Educational choices and family outcomes

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Educational choices and family outcomes

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Contents

CHAPTER 1

Introduction

Educational levels have increased considerably in the past decades, especially among women who are now graduating from college at higher rates than men (OECD, 2020*e*). Economists have long been concerned with the effects of education on various aspects of individuals' lives, such as earnings, fertility and health (e.g. Becker, 1964; Card, 1999; McCrary and Royer, 2011; Mincer, 1974; Monstad et al., 2008; Oreopoulos and Salvanes, 2011). The level of education is only a crude measure of educational attainment as fields of education differ in curriculum, skill requirements and labor market prospects. This has effects beyond pecuniary returns, which the literature has focused on so far (Altonji et al., 2012, 2016; Kirkebøen et al., 2016). Recent studies now also investigate outcomes other than earnings returns, such as partner choice and fertility (Kaufmann et al., 2015; Kirkebøen et al., 2020; Wiswall and Zafar, forthcoming).

Fields of study likely have large and heterogeneous effects on many family outcomes. Field of study may affect partner choice as the chosen field influences the pool of potential partners one meets while in education, but also subsequently in one's social and professional network. It may act as a signal of ability, social status and/or labor market potential, which affects individuals' attractiveness on the marriage market (Kaufmann et al., 2015). Types of education differ in their career prospects which may affect individuals' decision on whether and when to form a family as well as on family size. The rising college graduation rates among women outdate the traditional male breadwinner model and redefine the division of labor among couples. The effects of educational choices may also transmit across generations. For instance, children's educational achievement may be shaped by pecuniary returns to education, but also by the quality of the chosen partner (e.g. Black and Devereux, 2011; Holmlund et al., 2011). Individuals' relatives, e.g. their parents, may also benefit from the skills, knowledge and network that individuals acquired during their education.

Despite the obvious importance of educational choices on family outcomes, which may run via multiple potential pathways, not much empirical research has been done on this topic. The chapters in this dissertation aim to contribute to filling some of the gaps in the literature on the effects of educational choices on family outcomes. Chapter 2 studies the causal effects of field of study on family formation and children's educational achievement. Chapter 3 investigates how individuals' educational choices affect their within-household earnings potential and consequently the division of labor once children are born. Chapter 4 focuses on the effects of the child being a doctor on parental health as an indicator for the importance of information limitations for inequalities in health.

Chapter 2 studies the relationship between field of study and family outcomes. An extensive literature has shown that the level of education affects not only earnings, but also important family outcomes such as partner choice and fertility. Much less is known about the impact of field of study on family outcomes even though college graduation rates have increased considerably in the past decades (OECD, 2020*e*).

The chapter uses admission lotteries for oversubscribed university studies in the Netherlands that took place between 1988 and 1999. The study programs considered are medicine, dentistry, veterinary medicine and international business, which had admission lotteries with sufficient numbers of admitted and rejected applicants. Centrally-executed lotteries fully determined access to these four studies, creating exogenous variation in who is admitted to the program. Consequently, winners and losers of the first admission lottery are identical in terms of pre-treatment characteristics, such as ability, motivation and preferences. Using an instrumental variable approach, family outcomes of applicants who won the first admission lottery and completed their preferred field of study are compared with family outcomes of applicants who lost the first lottery and entered their next-best field.

The results show that winning the lottery and completing the desired study program has significant effects on individuals' partner choice (measured by level and field of education as well as earnings), (household) earnings and fertility. Moreover, there is evidence of intergenerational effects on children's scholastic achievement. The effects differ by lottery program and by gender indicating that the individual characteristics of the study program and the labor market they lead to are relevant for later-life outcomes.

Chapter 3 assesses how educational choices themselves and as determinants of within-household earnings potential affect individuals' labor market trajectories when having children. A recent literature shows that first-time parenthood has substantial and persistent negative effects on women's labor market outcomes, while there are only minor negative effects for men (e.g. Kleven et al., 2019*a,b*). The causes of this so-called 'child penalty' on women are still less clear. One potential cause brought forward in the literature is household specialization based on comparative advantage. Men often out-earn their female partners and may thus have a comparative advantage in labor market work relative to child rearing and household production, and specialize accordingly. On average, this would cause a parenthood earnings gap to the disadvantage of women as is found in the literature. If couples divide labor based on their comparative advantages, then households where the woman has the higher earnings potential should deviate from the traditional division of labor. Women with a high relative earnings potential should concentrate on market work and their partners on home production.

The chapter tests this hypothesis using administrative data for the Netherlands and an event-study methodology centered around the birth of the first child. The results first confirm previous studies that document a substantial child penalty on women and hardly any effects of fatherhood on men's labor market outcomes. Women's earnings loss is primarily driven by their marked reduction in working hours and to a lesser extent by lower participation and a gradual decline in wage rates. However, child penalties are heterogeneous with respect to individuals' level of education and field of study.

Importantly, analyses for various proxies of (relative) earnings potential show no evidence that households divide market work and child care based on comparative advantages or bargaining power. Women who have a higher earnings capacity than their partner face lower earnings losses after childbirth and reduce their labor supply less than women with a low relative earnings potential. However, men's labor market trajectories appear largely unaffected by parenthood irrespective of their relative earnings potential, which speaks against the importance of household specialization. These patterns seem instead be driven by differences in absolute earnings potential among women, such that higher-educated/higher-earning women remain more attached to the workforce after having children. Descriptive evidence suggests that they manage to reconcile career and family by making more use of formal child care.

Chapter 4 uses the admission lotteries to medical school in the Netherlands to study how health outcomes of parents are affected by having a child who is a doctor. This will provide insights about the importance of unequal access to medical expertise and services as a driver of inequalities in health, health care use and access. A large literature shows that even in the presence of universal health insurance coverage there remains inequality in access to health care for reasons unrelated to individuals' health (e.g. Angerer et al., 2019; Van Doorslaer et al., 2006, 2004). These reasons include information limitations about health risks, adequate preventive behavior or treatment options. Doctors' parents presumably have full access to medical expertise and services via their children, so that their health care is unaffected by any of these factors.

There are various ways in which parents' health care use and outcomes may be affected by having a child who is a doctor. Doctors may provide information about preventive behavior and health risks. They may also convince their parents to take prescribed medication and to complete treatments and may be able to recognize symptoms at an early stage. Lastly, doctors may use their knowledge and network to obtain treatment for their parents.

The chapter compares outcomes of the parents whose child won the first admission lottery to medical school and became a doctor to the outcomes of parents whose child lost this lottery and did not become a doctor. The health outcomes considered are mortality, (total) health care costs, different types of health care use and various hospital diagnoses and medication use. The findings document strong associations between the child being a doctor and parental health care use, costs and mortality in the Dutch population. Yet, when controlling for self-selection into the medical profession exploiting the randomization induced by the admission lotteries, these effects largely disappear. The estimation results show causal effects on mortality which are close to zero and statistically insignificant. For health care use and costs most estimates are not significantly different from zero, though some are too imprecisely estimated to rule out substantial effects. Overall, the results indicate that having access to medical expertise and services through a child who is a doctor is not an important cause of differences in parents' health care use and mortality.

CHAPTER 2

Field of study and family outcomes[1]

2.1 Introduction

A recently emerging literature shows that the causal effects of field of study on earnings are of similar magnitude as the causal effects of the level of education on earnings (Altonji et al., 2012; Hastings et al., 2013; Ketel et al., 2016, 2019; Kirkebøen et al., 2016). But while an extensive literature documents that higher levels of education not only affect earnings but also important family outcomes such as partner choice and fertility[2], much less is known about the impact of field of study on family outcomes. This paper contributes to filling this gap.

Field of study can influence family outcomes in various ways. First, it may affect partner choice as the chosen field influences the pool of potential partners at an age at which many partnerships are formed. There is indeed strong assortative matching by field of study (Bičáková and Jurajda, 2016; Eika et al., 2019). The chosen field of study also affects individuals' attractiveness on the marriage market as it may act as a signal of ability, social status and/or labor market potential (Kaufmann et al., 2015). Second, because fields of study differ in the impact they have on career opportunities, they may influence decisions on whether and when to form a family. Using Scandinavian data,

[1]This chapter is based on Artmann et al. (2018).

[2]Examples include: Oreopoulos and Salvanes (2011), Lefgren and McIntyre (2006), Currie and Moretti (2003), Geruso and Royer (2018), Fort et al. (2016), Monstad et al. (2008), McCrary and Royer (2011) and Aaronson et al. (2014).

Hoem et al. (2006) and Lappegård and Rønsen (2005) find that field of study serves as a better predictor of permanent childlessness and first-birth rates than the level of education. Third, through their effects on own earnings and partner quality, field of study may affect the educational achievement of children (e.g. Black and Devereux, 2011; Holmlund et al., 2011). Relatedly, Kaufmann et al. (2015) show that children of applicants who are admitted to a more elite university program in Chile perform better on a national standardized test.[3]

If the chosen field of study has effects beyond labor market outcomes, prospective students may be aware of this and take these effects into account when making their field of study choices. Wiswall and Zafar (forthcoming) present evidence that students at an elite university in the US indeed believe that their choice of major affects the probability of being married, spousal education and earnings, and fertility. Moreover, they find that the perceived family returns help explain students' human capital choices.

Whether differences in family outcomes by field of study are truly causal or are merely due to self selection, is an open question. While the above mentioned channels are plausible, it cannot be ruled out that people who are anyhow less inclined to have a family, opt for a field of study where a higher fraction of people stay single. Also Wiswall and Zafar's finding that students perceive that family outcomes depend on the choice of major, does not prove causality because only the realization for the actually chosen major is observed.

This paper uses admission lotteries for university studies in the Netherlands to estimate causal effects of field of study on family outcomes. The effects that we estimate are based on the contrast between family outcomes of applicants who won the admission lottery and completed their preferred field of study and family outcomes of applicants who lost the lottery and ended up in their next-best field. The family outcomes that we consider are: having a partner, quality of the partner (measured as having a partner with a university degree and having a partner with a university degree from the same field), own earnings, partner earnings and household earnings, number of children and quality of children (measured as children entering the highest track in secondary school). We focus on medicine, dentistry, veterinary medicine and international busi-

[3] Kaufmann et al. (2015) also study effects on the likelihood of marriage and of having a child, but do not find any effects. They find positive effects on spouse quality for female, but not male applicants.

ness studies, which are undergraduate programs that have admission lotteries with sufficient numbers of admitted and rejected applicants.

The labor markets for which the four programs prepare their students are differently organized which may affect their impact on partner choice and other family outcomes. Completing medicine, dentistry and veterinary medicine grants a license that is required to work in a specific occupation. This is not the case for international business studies, which shares its work field with economics and regular business administration. Students who complete medicine often start working in large organizations such as hospitals, while dentists and vets are mainly self-employed. Dentists, and to a lesser extent medical doctors, have much higher incomes than veterinary doctors.

The admission lotteries provide an opportunity to estimate the causal effects of completing a particular field of study. They also allow us to examine some potential mechanisms that drive the choice of a partner. We can distinguish between the impact of the field of study on having a partner from the most-preferred field of study, i.e. the lottery study program, and on having a partner from the same field of study. If partner choice is mainly determined by who someone meets during her/his study, we should find a strong causal effect of winning the admission lottery on having a partner from the most-preferred field of study, but not on having a partner from the same field of study. This pattern of causal effects also occurs when individuals have preferences for a partner with the same (realized) study background. On the other hand, if individuals have a strong preference for partners with the same (pre-lottery) interests then we should find no causal effects of having a partner from the most-preferred field of study, but a strong causal effect on having a partner from the same field of study. Losing a lottery may, however, not change preferences for a partner from that field of study, but may make someone less attractive to potential partners in that field. Finally, partner choice may be related to labor market prospects. In that case causal effects should mainly be present for students in medicine en dentistry, which have the highest returns.

Our results show that losing the lottery significantly reduces the probability to be with a partner from the most-preferred field of study. This holds for both men and women in all fields of study. In most cases this effect has about the same size as the causal effect on having a partner from the same field of study. This suggests that people have a stronger preference for having a partner from their most-preferred field of study than having a partner from the same field of study, but that when someone loses the admission lottery it becomes more difficult to find a partner from the most-preferred field of study. For women there are no effects on the likelihood of having a partner and for men this effect is only significant for medicine and veterinary medicine. Women who complete the medical studies on average have partners with higher earnings, this does not hold for men and for women completing international business. Men who complete medicine have more children than their counterparts. The children of men who complete medicine and of women who complete veterinary medicine or international business are more likely to enter the highest track in secondary school than the children of their counterparts. The finding that fields of study matter for family outcomes is further strengthened by the result that the effects of winning the lottery for medicine depend on what the next-best field of study is.[4]

The analysis based on admission lotteries pertains to four fields of study. To put these results in perspective, Section 2.2 starts with a descriptive analysis using administrative data from 16 birth cohorts (1967-1982) of the Dutch population. This analysis documents considerable differences in family outcomes between fields of study among university graduates for *all* fields of study. Probabilities to have a partner vary by more than 10 percentage points between different fields and the degree of assortative matching by field of study is high. Graduates from different fields of study have partners with on average rather different earnings and fertility and educational outcomes of their children differ substantially between graduates from different fields of study. After this descriptive section, Section 2.3 provides details about the admission lotteries, Section 2.4 introduces the empirical approach and Section 2.5 describes the data. Section 2.6 presents the estimates of the causal effects of fields of study on family outcomes. Section 2.7 presents results that differentiate the effects of completing medicine by next-best fields. Section 2.8 summarizes and concludes.

2.2 Family outcomes by field of study

This section presents descriptive results of family outcomes by field of study. It first shows high rates of assortative matching by field of study. Next, it documents substantial differences between graduates from different fields of study in own earnings, partner

[4] Medicine is the only field with admission lotteries with enough observations to analyze this.

earnings and household earnings, as well as in fertility and the educational achievement of their children.

Data and setting

The results in this section are based on administrative data from Statistics Netherlands (CBS) which contain information from municipalities, tax authorities, education registries and social insurance administrations of all inhabitants of the Netherlands.

We distinguish between 11 fields of study at the university level: 1) Education, 2) Humanities, including Arts and Journalism, 3) Social sciences, 4) Economics, 5) Business, 6) Law, 7) Science, including Mathematics and Informatics, 8) Engineering, including Manufacturing and Construction, 9) Agriculture, including Veterinary, 10) Health, and 11) Services.[5] Students in the Netherlands choose their field of study when they enter university, around age 18. We focus on the cohort born between 1967 and 1982 (4.3 million individuals) and measure outcomes at age 35. At this age, earnings provide a good proxy of life-cycle earnings and most family formation has taken place.[6]

Like in many other countries, enrollment in university education in the Netherlands increased substantially over time, from about 9.4% of men and 7.8% of women born in 1967 to approximately 12.8% of men and 14.7% of women in the 1982 birth cohort. For both men and women there are only minor differences in distributions of fields of study between cohorts. When looking at differences between fields we therefore pool all cohorts.[7] Gender differences in choice of field of study are substantial (see Figure 5 in the Appendix), and similar to observed differences in most OECD countries (OECD, 2016). Business and Engineering are popular fields among men and Social sciences and Humanities are often chosen by women.

Partner choice and earnings

The probability to have a partner (married or cohabiting) at age 35 is higher for male university graduates than for other men (79.6% vs. 74.7%), while there is only a minor

[5]In an earlier version of this paper we distinguished between at least college and less than college (see Artmann et al. (2018)). This does not change our findings.

[6]Although fertility is not completed at age 35, potential differences in the timing and number of children by field should be visible at that age.

[7]See Figure 5 in the Appendix for the distributions of fields of study among university graduates by gender for the birth cohorts 1967-1972, 1973-1977 and 1978-1982.

difference for women (81.2% vs. 81.9%). About 5.7% of men and 5.3% of women are in a partnership where both partners are university-educated. This fraction is more than four times as large as what would result under random matching.[8] There are also differences by field of study. While more than 84% of graduates in Health and female graduates in Agriculture and Veterinary have a partner at age 35, just around 73% of male graduates in Humanities and Social Sciences do.[9]

When we focus on couples where both partners completed university, we find that around 28.2% of men and women are in a partnership where both partners have a degree from the same field of study. This is a much larger share than the less than 10% that would result under random matching.[10]

To compare assortative matching between fields we use the measure proposed by Liu and Lu (2006) which takes differences in marginal distributions into account.[11] Figure 1 shows these corrected shares of assortative matching by field of study and gender. For men, the corrected shares are highest in Engineering and for women in Health, while for both genders they are lowest in Services, Business and Education.

Individual earnings differ substantially by level of education and gender. At age 35, men with a university degree earn on average 60,300 euros per year and men without a university degree 35,800 euros.[12] For women these amounts are 41,000 and 18,600 euros. When looking at household earnings, the gender differences largely disappear. Women's

[8] To calculate the share of men in a partnership where both partners are university educated under random matching, we multiply the share of university-educated men in their birth cohort with the share of women with a university degree in the birth cohort of the men's actual partner. Taking the mean of the resulting probabilities gives men's likelihood under random matching of both partners having a university degree. The shares for women are computed analogously.

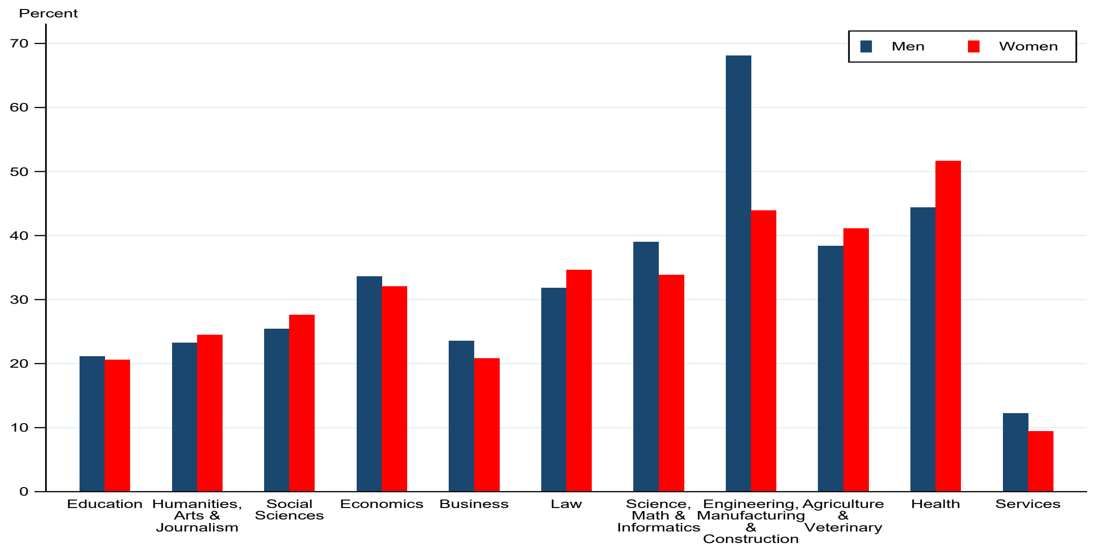
[9] Figure 6 in the Appendix shows the probability to have a partner/be married/be divorced by gender for all fields of study. Partners also include same-sex partners. Marriage rates are roughly 30 percentage points lower than partnership rates. Divorce rates are low at age 35, only 4.6% (2.6%) for women (men).

[10] Figure 7 in the Appendix shows for each field of study the actual and random shares with a partner from the same field of study by gender. The random matching draws from the cohort of the current partner. For all fields, the observed share of graduates with a partner from the same field is considerably higher than the share that would be expected under random matching.

[11] While the sex that is in the minority in a given field can in principle achieve an assortative matching rate of 100%, the maximum attainable rate for members of the sex that is the majority in a given field is bounded by the "supply" of the other sex. Liu and Lu (2006) divide the difference between the actual share and the share under random matching by the difference between the maximum attainable share and the share under random matching.

[12] Annual earnings are measured as the sum of before-tax income from employment, income from self-employment, income from abroad, and other income from labor and are converted to 2015 euros. Household earnings are calculated including single households.

Figure 1: Shares of graduates with a partner from the same field (applying Liu and Lu (2006) correction)

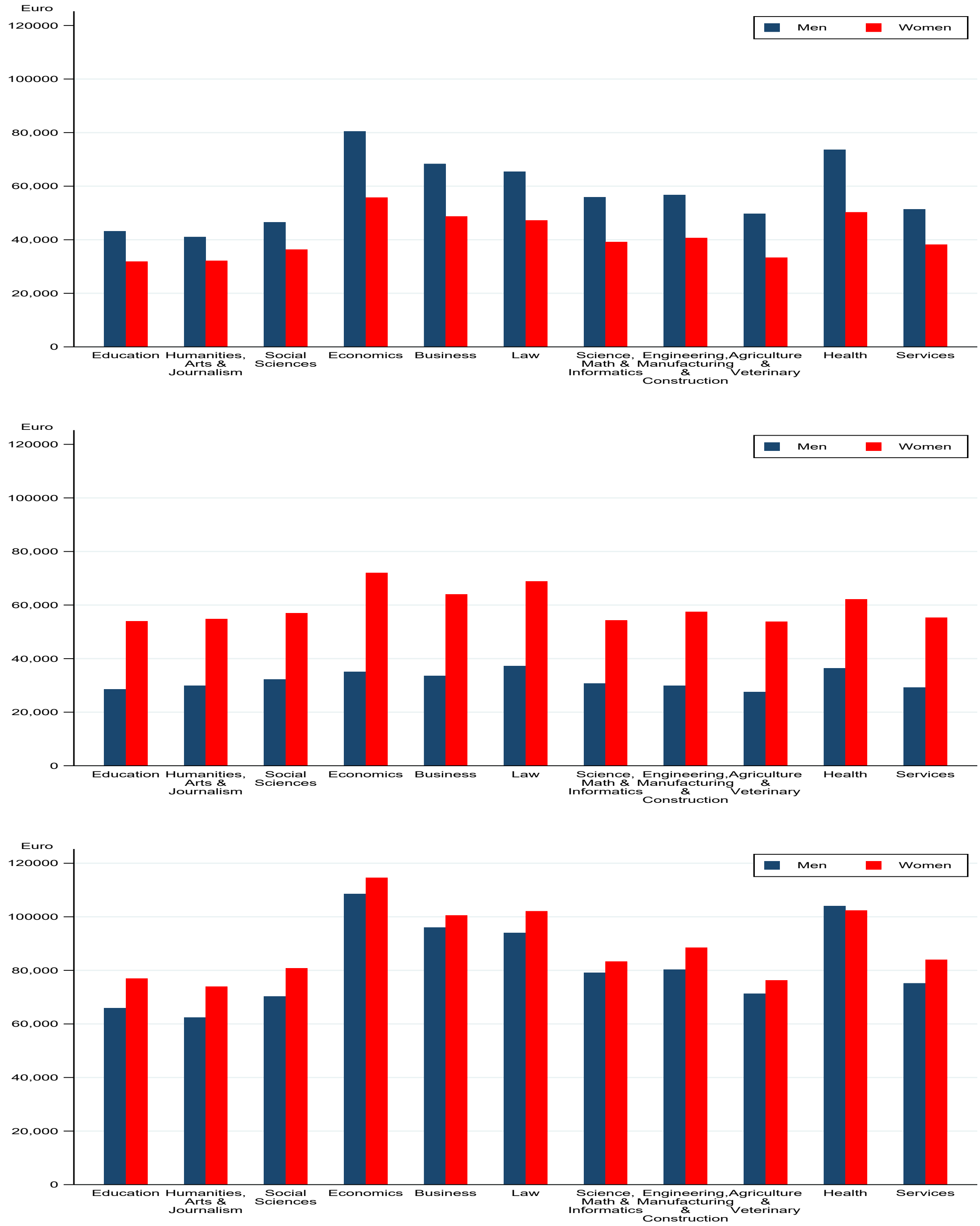


households earn slightly more than the respective households of men with the same level of education, i.e. household earnings are 88,800 vs. 85,500 for university-educated and 53,600 vs. 50,000 euros for non-university educated women and men. This pattern is likely to reflect the high degree of assortative matching documented and women's tendency to "marry up" in terms of education, age and income (Bertrand et al., 2015).

The top panel of Figure 2 shows that individual earnings are much higher for graduates from some fields (Economics, Health, Business, Law) than for graduates from other fields (Education, Humanities). In each field, individual earnings are higher for men than for women. The middle panel shows that partner's earnings follow the same pattern by field and the reverse pattern by gender: women who studied Economics or Law match with partners who earn substantially more than the partners of women in Education. The bottom panel combines the two graphs (together with partner formation) and shows that the differences in household income between graduates from different fields are inflated, whereas the differences between men and women disappear.[13] The fact that the differences between fields are inflated is a likely consequence of the high degree of assortative matching by field of study.

[13]The fact that in most fields household earnings are higher for women than for men reflects that women typically form a partnership with men that are somewhat older.

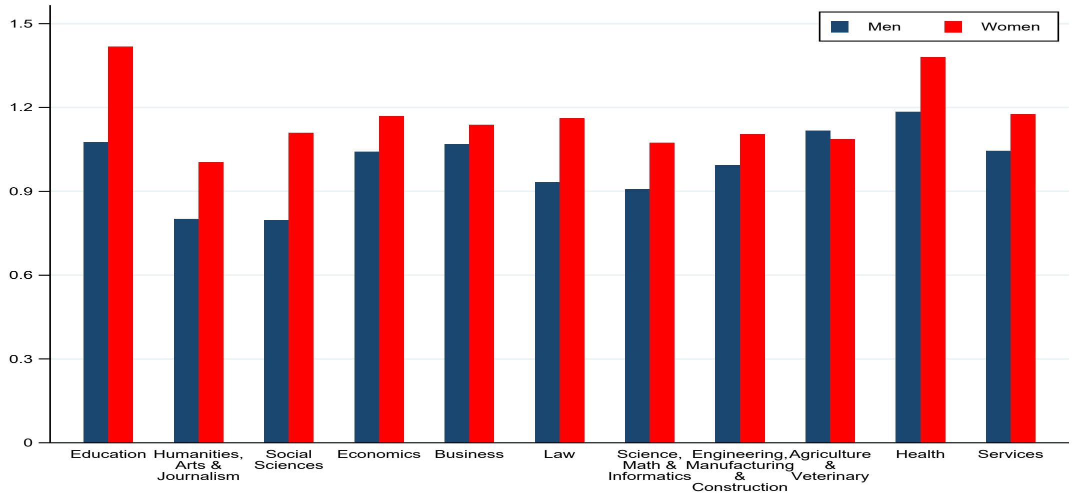
Figure 2: Average individual (top panel), partner (middle panel), and household (bottom panel) earnings at age 35 by field of study



Intergenerational effects

Figure 3 shows the average number of children at age 35 by field of study and gender. Women of all fields have on average more children at age 35 than men from the same field.[14] Female graduates in Education and Health and male graduates in Health have the most children, while graduates in Humanities, the field with the lowest average (household) earnings, have the fewest. The average number of children tends to be higher in fields where a larger fraction of the graduates have a partner.

Figure 3: Average number of children at age 35 by field of study

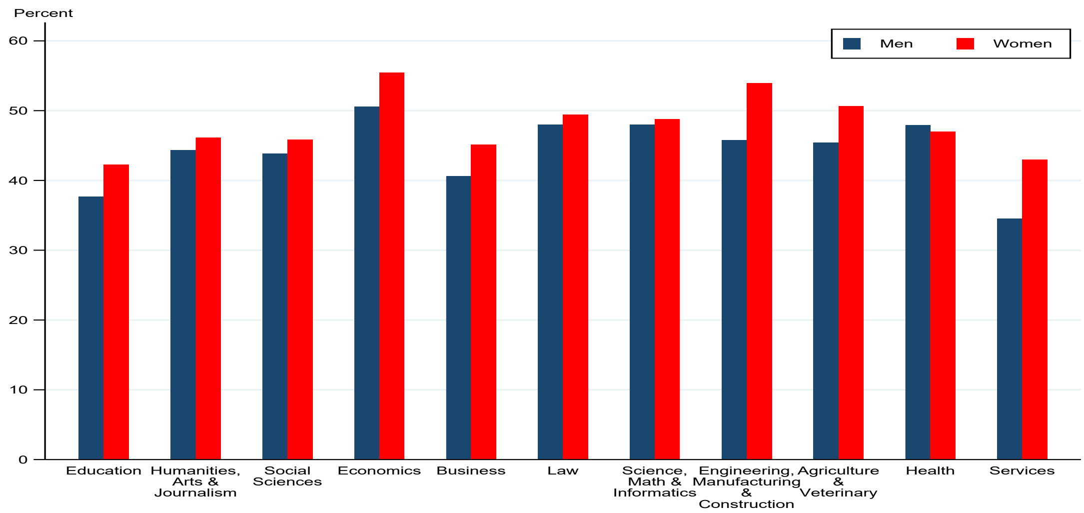


To examine the educational success of the children of graduates from different fields of study, we focus on children that are of secondary-school age and measure which share of them entered the highest academic track.[15] Slightly more than 20% of each cohort from the general population enters this track. Figure 4 shows that this share is higher among the children of parents with a university degree. It also shows that there is substantial variation across fields. About 35% of the children of men who studied Services enter the highest track, while this share is about 55% among the children of female graduates in Economics or Engineering.

[14]The differences by field of study in average number of children at age 40 of the birth cohorts 1967 to 1975 show a qualitatively similar picture.

[15]Dutch schoolchildren are tracked into different levels at age 12 when they enter secondary school. The pre-university track is the highest academic track.

Figure 4: Fraction of secondary-school children that entered the highest academic track by field of study



2.3 The admission lotteries

The previous section documented large differences in family outcomes by field of study. Whether these differences reflect causal effects of fields of study or are merely due to selection, is unclear. To examine this, we now turn to fields of study that have used admission lotteries.

Secondary-school graduates in the Netherlands who complete the pre-university track are eligible for university studies in all fields of study and institutions. For the large majority of fields, universities have to accept all applicants but some fields have quotas that limit the number of students that are admitted. The quotas were introduced in response to the drastically increasing number of potential students at the end of the 1960s which exceeded the number of available places (see Goudappel (1999) for details on the reasons for introducing quotas).

Until 1999, students who applied to a study program with a quota were admitted on the basis of the results from a (nationwide) centralized lottery.[16] We focus on medicine,

[16]From 2000 onwards, studies with quotas have been allowed to admit (initially) at most 50 percent of the students using their own criteria. Universities have made increasing use of this and by now, the admission lotteries have been completely abandoned. Selection is often based on motivation and previous experience. For this reason we restrict our analysis to students who first applied to a lottery study before this change.

dentistry, veterinary medicine and international business, which are the study programs that were substantially oversubscribed for multiple years. The latter is important because rejected applicants are allowed to reapply in the next year. We observe that a substantial fraction of rejected first-time applicants reapply at least once.

Lottery participants are assigned to lottery categories.[17] Those with a higher GPA on their high-school exams have a higher chance of being admitted, i.e. they receive a higher weight in the lottery (see Table 1).[18] Applicants in lottery category A with a GPA of at least 8.5 receive a weight of 2.00, whereas applicants with a GPA between 6 and 6.5 are assigned to category F with a weight of 0.67. The last category "Other" includes applicants who did not take the Dutch secondary school exams, e.g. foreign students, and will be excluded from the analysis. The majority of students are in categories D to F. The number of available places per category is determined such that for the total number of available places divided by the number of applicants in a category, the weights given in Table 1 hold.

Table 1: Lottery categories

Category	GPA	Weight	Share			
			Medicine	Dentistry	Vet. medicine	Int. business
A	$8.5 \leq GPA \leq 10$	2.00	1.7%	0.3%	1.0%	0.7%
B	$8.0 \leq GPA < 8.5$	1.50	5.4%	1.9%	2.8%	2.9%
C	$7.5 \leq GPA < 8.0$	1.25	8.6%	3.4%	6.4%	6.4%
D	$7.0 \leq GPA < 7.5$	1.00	20.8%	13.8%	18.7%	19.2%
E	$6.5 \leq GPA < 7.0$	0.80	22.1%	21.4%	24.7%	24.4%
F	$6.0 \leq GPA < 6.5$	0.67	29.9%	39.8%	33.3%	36.1%
Other	–	1.00	11.5%	19.5%	13.2%	10.4%

Note: GPA is grade point average on the final exams in high school. Share is the share of applicants in the different categories that applied for the lotteries in the years 1988 to 1999. Weight indicates the relative probability of being admitted. The category "Other" refers to students who did not participate in the nationwide high school exams, such as foreign students. This category will be excluded from the analysis.

[17] Applicants are allowed to submit a list of their up to three most preferred universities, but their choice has no influence on the outcome of the admission lottery. After the result of the lottery is known, admitted students are divided over the universities taking account of their preferences as far as possible.

[18] Graduating from secondary school requires an exam in seven subjects including Dutch and English. Applicants for medicine, dentistry and veterinary medicine should also have passed biology, chemistry, physics and math. Once the exam is passed it cannot be retaken.

Comparison of lottery participants with general university population

In most years between 1988 and 1999, the lottery participants in our sample account for about 8 to 11% of all first-year university students. For the field of health, the number of lottery participants in medicine and dentistry equals on average 117% of all first-year university students in this field.[19]

To assess whether our sample of lottery participants is similar to the general university population, Table 2 compares the two groups in terms of family background. In terms of numbers of siblings, parents living together and urbanicity there are no large differences between the lottery sample and the general population. Participants in the lotteries for medical school, dentistry and veterinary medicine come from more affluent families than the typical university student (in their field). This is not the case for participants in the lotteries for international business, who seem to come from average families with children graduating from university.[20] Hence, while we cannot claim that the lottery sample is representative for the general university population, it does not seem to be a very exceptional group.

[19]Note that this does not reflect the actual distribution of medicine and dentistry students within the field of health as not all lottery participants actually enroll in that field. The lottery participants (including those we drop from our sample, see Section 2.5) enrolling in medicine or dentistry account for about 48% of first-year university students studying a health-related program between 1988 and 1999.

[20]The share of students for whom the parents are both unknown is larger in the general university population than in the lottery sample. This is due to the restriction for inclusion in the lottery sample of having participated in the Dutch high-school exams.

Table 2: Family background characteristics

	Men				Women			
	Siblings	Parental earnings	Parents cohab./ married	Urban	Siblings	Parental earnings	Parents cohab./ married	Urban
I. University graduates								
Education	1.88	48,742	86.5%	56.7%	1.83	55,412	86.9%	54.8%
Humanities, Arts, Journalism	1.78	56,501	83.8%	60.7%	1.68	59,501	83.2%	61.3%
Social sciences	1.71	58,153	82.1%	63.4%	1.70	62,454	82.4%	62.0%
Economics	1.66	62,195	88.3%	58.6%	1.64	64,465	87.9%	57.0%
Business	1.71	62,836	87.5%	58.3%	1.67	61,442	85.9%	57.1%
Law	1.70	66,411	84.6%	64.4%	1.68	65,788	84.6%	63.3%
Science, Math., Informatics	1.68	56,909	87.1%	59.1%	1.66	58,994	86.8%	59.9%
Engineering, Manuf., Constr.	1.70	56,612	89.4%	55.2%	1.64	65,211	89.0%	56.1%
Agriculture, Veterinary	2.07	50,171	90.4%	36.4%	1.75	60,839	87.2%	50.7%
Health	1.82	68,349	87.7%	61.0%	1.81	64,951	87.6%	56.8%
Services	1.66	53,829	84.6%	57.2%	1.61	58,083	87.5%	53.1%
II. Lottery participants								
Medicine	1.83	79,106	88.3%	63.2%	1.77	76,885	88.4%	59.4%
Dentistry	1.67	87,238	89.8%	60.9%	1.64	87,599	91.8%	58.2%
Veterinary medicine	1.85	65,743	90.0%	44.1%	1.67	69,003	88.7%	52.9%
International business	1.62	60,015	85.9%	60.9%	1.58	63,643	86.6%	58.5%

Note: The number of siblings includes half-siblings. Average parental earnings are measured as the sum of maternal and paternal earnings in 1999. Parental cohabitation/marriage rates are measured when the individual is aged 17. Urbanicity is measured as the fraction of mothers (the father is used if the mother cannot be linked in the records) living in an urban area in 1995.

2.4 Empirical approach

We are interested in the effects of completing a study with an admission lottery on family outcomes. As in Section 2.2, we focus on outcomes measured at age 35. We assume a linear relationship between outcome variable Y_{it} of individual i observed at age 35 in year t, and degree completion (C_i):

$$Y_{it} = \alpha_t + \delta C_i + X_i \beta + LC_i + U_{it} \tag{2.1}$$

The effects of degree completion on outcomes are captured by δ, our parameter of interest. The vector of controls X_i includes individual's age at first lottery participation and an indicator for non-western origin.[21] The interaction term between lottery category and year of first participation, LC_i, controls for the fact that individuals' chances of being admitted are only identical conditional on fixed effects for lottery year times category. Lastly, α_t are fixed effects for the year in which the respective outcome is observed and U_{it} is an individual-specific error term.

Compliance with the result of the first lottery is imperfect for all four study programs (see Section 2.5). Not all winners of the first lottery enroll in the respective program, while some drop out before completing their degree. The fraction of lottery losers who (successfully) reapply in subsequent years differs by program, but ultimately a substantial fraction of first-time lottery losers completes the lottery study program. As degree completion C_i is endogenous, a simple OLS estimate of δ would be biased, so that we use an instrumental variable approach. The result of an individual's first lottery (LR_{1i}) serves as an instrument for degree completion (C_i):

$$C_i = \kappa_t + \lambda LR_{1i} + X_i \theta + LC_i + V_{it} \tag{2.2}$$

The identifying assumption is that conditional on X_i and LC_i, the result of the first lottery is mean independent of U_{it}: $E[U_{it}|X_i, LC_i, LR_{1i}] = E[U_{it}|X_i, LC_i]$. Since program admission is random conditional on lottery category times year of first participation, the mean conditional independence assumption holds for the first lottery where selective reapplication has not taken place yet. The parameter λ describes the fraction

[21] When analyzing the effect of completing a specific lottery study program on children's educational achievement we also include the child's gender, child's age at secondary-school enrollment and fixed effects for the year of enrollment in X_i.

of compliers in the sample, so that δ in equation (2.1) is to be interpreted as Local Average Treatment Effect (LATE). This describes the effect of graduating for individuals for whom the result of the first lottery determines whether they complete the respective study program.

2.5 Data

Data sources and sample

We use administrative data from different registers available at Statistics Netherlands. The register on the admission lotteries contains information on all applicants for medicine, dentistry, veterinary medicine, and international business, their lottery category and the outcomes of all lotteries. We merge this with information on actual study choices of all applicants and their study progress.

Lottery information is available for the years 1987 to 2004. To make sure that we observe first-time applicants, we exclude applicants who participated in 1987 since we have no information about possible participation in 1986, and we exclude applicants older than 20 when we observe them applying for the first time. Because the lottery system was gradually abandoned after 1999, we also exclude individuals applying for the first time after that year.[22]

Summary statistics

The lotteries ensure that characteristics of winners and losers of their first lottery are well balanced. This is confirmed by the results from balancing tests reported in Tables 13 to 16 in the Appendix for each of the four study programs. Table 3 reports summary statistics on study enrollment and completion separately by gender and result of the first lottery for the four study programs. Around 93% of the applicants admitted to medicine, dentistry and veterinary medicine in their first lottery actually enroll in the program, while these rates are slightly lower for international business. Among the losers of the first lottery, between 11% and 43% of men and 10% to 48% of women enroll in the respective program after having won a subsequent lottery. Almost all lottery

[22]We also drop applicants from lottery category A and applicants for dentistry in 1988 to 1992 and for international business in 1993, 1994 and 1999 because for these groups admission probabilities are close to one.

winners enroll in a study program in the Netherlands, while between 90% and 98% of the losers do so. The shares of lottery winners who complete the program are lowest for international business (55% of men and 60% of women) and highest for medicine (81% of men and 84% of women). Between 88% and 98% of lottery winners and between 83% and 97% of lottery losers complete a study program in the Netherlands.

Table 3: Sample description by gender and result of the first lottery application

	Men		Women	
	Winners	Losers	Winners	Losers
I. Medicine				
Enrolled in medicine	94.6%	42.9%	93.6%	48.2%
Completion of medicine	81.3%	37.4%	83.9%	44.6%
Enrolled in study program in NL	99.6%	96.5%	99.6%	97.4%
Completion of study program in NL	95.6%	90.6%	98.1%	95.5%
N	4872	5697	6854	7970
II. Dentistry				
Enrolled in dentistry	91.5%	39.7%	91.7%	42.3%
Completion of dentistry	76.9%	34.1%	81.1%	38.8%
Enrolled in study program in NL	99.5%	96.5%	99.5%	98.7%
Completion of study program in NL	96.8%	92.6%	98.6%	96.8%
N	437	511	444	529
III. Veterinary medicine				
Enrolled in veterinary medicine	93.7%	24.9%	93.7%	32.0%
Completion of veterinary medicine	76.8%	22.4%	83.8%	28.2%
Enrolled in study program in NL	98.9%	90.6%	99.4%	93.3%
Completion of study program in NL	94.3%	83.1%	97.9%	88.7%
N	349	960	678	1922
IV. International business				
Enrolled in international business	86.9%	11.5%	83.3%	10.1%
Completion of international business	54.5%	6.4%	60.0%	6.2%
Enrolled in study program in NL	99.1%	98.6%	99.4%	97.6%
Completion of study program in NL	88.6%	86.3%	93.8%	90.4%
N	3001	2492	1396	1091

Table 4 shows for each of the lottery studies the five fields of study that are most often chosen by male and female lottery losers who end up in their next-best study. Many losers enroll in programs that belong to the same educational field as the lottery study program they applied for.

Table 5 presents summary statistics for the outcome variables by program, gender and admission status. Between 41% and 56% of the lottery applicants have a partner with a university degree at age 35, whereby this fraction is higher among lottery winners than among losers. The winners of all four lottery study programs more frequently have a partner who obtained his/her university degree in the same ISCED-classified educational field. Admitted first-time applicants also more often have a partner who graduated from the respective lottery study program. Average annual real earnings at age 35 are higher for lottery winners than for lottery losers. The partners of male lottery losers often earn more than those of male lottery winners, while the reverse holds for female lottery applicants. Overall, the households of lottery winners have higher average incomes than the households of lottery losers, with the exception of women applying for veterinary medicine.[23] The fraction of medicine, dentistry, veterinary medicine and international business applicants' children who enroll in the highest track of Dutch secondary education also partly differs between lottery winners and losers.

2.6 Results

This section first shows that the result of the first lottery is decisive for the study choice of 37% to 54% of the applicants. It then shows that field of study affects partner choice. Doctors, male veterinarians and female international business graduates are more likely to have a partner (with a university degree) than the respective applicants who were not admitted. Winning applicants from all fields are more likely to have a partner from the same field of study than losing applicants, and female doctors and female veterinarians have partners who on average earn more than the partners of applicants that lost the lottery for these fields. Finally, this section shows that field of study influences the number of children and the likelihood that children perform well in school.

[23] The lottery applicants' and their partners' earnings do not add up to the respective average household income as the latter also includes single households.

Table 4: Most popular study fields of lottery losers enrolling in other programs

Men		Women	
I. Medicine			
Health	23.0%	Health	31.2%
Science, Mathematics, Informatics	19.5%	Social sciences	16.6%
Business	13.6%	Science, Mathematics, Informatics	13.8%
Engineering, Manufacturing, Construction	9.9%	Business	8.3%
Law	9.2%	Education	7.9%
II. Dentistry			
Health	27.6%	Health	34.7%
Business	19.8%	Science, Mathematics, Informatics	12.0%
Engineering, Manufacturing, Construction	13.8%	Law	10.7%
Science, Mathematics, Informatics	11.6%	Business	10.4%
Law	7.2%	Social sciences	8.5%
III. Veterinary medicine			
Agriculture, Veterinary	23.2%	Science, Mathematics, Informatics	21.3%
Science, Mathematics, Informatics	22.0%	Health	19.7%
Health	12.2%	Agriculture, Veterinary	18.9%
Engineering, Manufacturing, Construction	12.2%	Education	7.8%
Business	9.3%	Social sciences	7.1%
IV. International business			
Economics	34.7%	Business	33.0%
Business	32.9%	Economics	26.1%
Law	10.1%	Law	14.0%
Social sciences	4.1%	Social sciences	7.5%
Engineering, Manufacturing, Construction	3.2%	Humanities, Arts, Journalism	5.7%

First-stage results

The first-stage regressions show the effects of winning the first lottery on the probability of completing the respective lottery study program. As displayed in the first lines of each panel in Table 6, the first-stage estimates are all highly significant and the F-statistic is always sufficiently large. Winning the first lottery increases the probability to complete medicine by 41 percentage points for men and by 37 percentage points for women, while the probability to complete dentistry rises by 43 percentage points for men and women. Winning the first lottery raises the likelihood to complete veterinary medicine by 49 percentage points for men and by 54 percentage points for women, whereas male

Table 5: Summary statistics on family outcomes by applicants' admission status and gender

	Men		Women	
	Winners	Losers	Winners	Losers
I. Medicine				
Partner at age 35	84.2%	81.7%	83.8%	84.4%
Partner university degree	54.9%	52.3%	55.7%	54.0%
Partner same university field	28.4%	21.4%	21.3%	17.1%
Partner medical degree	23.0%	14.8%	17.7%	11.1%
Number of children at age 35	1.24	1.10	1.42	1.39
Real (2015) earnings	82,775	69,890	63,526	52,758
Real (2015) earnings partner	37,878	39,002	72,212	68,154
Real (2015) household earnings	114,335	101,192	123,527	109,431
Child enrolled in highest track	54.5%	51.0%	56.5%	56.0%
II. Dentistry				
Partner at age 35	85.5%	83.3%	86.2%	88.1%
Partner university degree	53.7%	52.4%	54.5%	54.8%
Partner same university field	28.5%	20.2%	24.4%	22.2%
Partner dentistry degree	17.9%	10.9%	18.0%	10.4%
Number of children at age 35	1.22	1.11	1.53	1.44
Real (2015) earnings	116,020	90,103	80,062	62,557
Real (2015) earnings partner	41,977	41,810	77,164	74,918
Real (2015) household earnings	151,719	124,035	146,230	127,790
Child enrolled in highest track	47.8%	51.6%	55.3%	47.9%
III. Veterinary medicine				
Partner at age 35	85.0%	81.0%	78.9%	81.5%
Partner university degree	50.9%	45.3%	41.9%	41.5%
Partner same university field	27.5%	15.5%	16.2%	12.8%
Partner veterinary medicine degree	24.2%	9.3%	12.9%	4.5%
Number of children at age 35	1.15	1.02	1.16	1.16
Real (2015) earnings	64,524	59,763	36,816	39,200
Real (2015) earnings partner	31,995	33,360	60,203	57,151
Real (2015) household earnings	91,477	86,381	84,019	85,260
Child enrolled in highest track	53.6%	48.3%	49.6%	47.0%
IV. International business				
Partner at age 35	81.2%	82.5%	84.0%	82.7%
Partner university degree	42.6%	40.6%	55.1%	53.3%
Partner same university field	10.0%	8.7%	19.0%	18.4%
Partner international business degree	5.0%	1.9%	11.4%	3.9%
Number of children at age 35	0.95	0.97	1.18	1.20
Real (2015) earnings	75,277	73,297	52,945	50,017
Real (2015) earnings partner	35,899	36,185	78,542	77,768
Real (2015) household earnings	103,915	102,540	118,241	113,339
Child enrolled in highest track	49.5%	50.4%	58.3%	54.2%

Note: We have weighted observations by the inverse probability of winning the lottery for each lottery category/lottery year combination to allow for a causal interpretation of the differences between the columns.

and female winners of the first lottery are 47 and 53 percentage points, respectively, more likely to complete international business.

The second lines in each panel in Table 6 show that redefining the treatment variable as enrollment instead of completion increases the first-stage estimates somewhat, from 0.44 for women participating in the lottery for medicine to 0.74 for men participating in the lottery for international business studies. This means that IV estimates of effects of enrollment are 16% to 37% smaller than IV estimates of effects of completion. To keep results comparable with the descriptives from Section 2.2 and because completion is a clearer treatment than enrollment, we will present IV results in terms of the effects of completion.

Effects on partnership formation and partner choice

The first rows in each panel of Table 7 report IV estimates of the effect of completion of a lottery study on the probability of having a partner. Men who completed medicine or veterinary medicine are 7 and 9 percentage points more likely to have a partner at age 35, respectively, than men who lost the lottery and ended up in their next-best study. It seems that the prestige of their job makes male doctors and veterinarians more attractive on the marriage market, while we find no such effect for females. There is also no effect for applicants of the other lottery studies.[24]

The next rows report the effects of completing lottery studies on the probabilities to have a partner with a certain level or type of education. We analyze whether an applicant's partner has 1) a university degree, 2) a university degree from the same broad field of study as the applicant[25] and 3) a degree from the same lottery study program as the applicant. All effects are measured unconditional on having a partner.

First, we find positive effects of degree completion on the probability to have a partner with a university degree for male and female doctors and for female international business graduates. Though marginally insignificant, the effect is largest in terms of magnitude for veterinary medicine. This is likely due to the fact that male lottery losers are somewhat more likely to not study at all or to study at a university of applied

[24] Table 17 in the Appendix reports the effects on the probability to be married (including registered partnership but not cohabitation) at age 35. We find significant positive (negative) effects for male doctors and dentists (female veterinarians), but none for the remaining graduates. There are only small negative (positive) effects on the probability to be divorced by age 35 for female graduates of international business (veterinary medicine).

[25] For the latter outcome we again use the ISCED-classification and sort fields of study into the same eleven mutually exclusive categories as in our descriptive analysis in Section 2.2.

Table 6: First-stage estimates

	Men			Women		
	$\hat{\lambda}$	s.e.	F	$\hat{\lambda}$	s.e.	F
I. Medicine						
Completion	0.41***	(0.01)	2013.1	0.37***	(0.01)	2363.1
Enrollment	0.50***	(0.01)	3813.4	0.44***	(0.01)	3991.7
II. Dentistry						
Completion	0.43***	(0.03)	189.0	0.43***	(0.03)	193.2
Enrollment	0.53***	(0.03)	362.4	0.50***	(0.03)	307.3
III. Veterinary medicine						
Completion	0.49***	(0.03)	333.5	0.54***	(0.02)	733.8
Enrollment	0.66***	(0.03)	668.0	0.60***	(0.02)	961.4
IV. International Business						
Completion	0.47***	(0.01)	1585.6	0.53***	(0.02)	913.2
Enrollment	0.74***	(0.01)	5669.2	0.71***	(0.02)	2197.8

Notes: All specifications include controls for ethnicity, age at the first lottery application, lottery category, year of first lottery and interaction terms of the year of first lottery and lottery category.
Levels of statistical significance: * p<0.10, ** p<0.05, *** p<0.01

sciences compared to lottery losers of the other programs. Lottery winners therefore have comparatively more opportunities to meet potential partners with a degree from a research university.

Second, there is a strong positive impact on the likelihood to have a partner who completed a university study in the same ISCED-classified field as the applicant, which for the lottery losers means having a partner educated in their second-best field ("Partner same field (uncorrected)"). When we account for the applicant's gender being in the minority or majority in the field and for the different sizes of fields (following the transformation proposed by Liu and Lu (2006)), the magnitude (and sometimes significance) of the estimates changes ("Partner same field (corrected)"). From the perspective of the prospective student who chooses a field of study, the uncorrected measure is probably the more relevant one as this is informative about the probability to have a partner who graduated university from the same field of study. The uncorrected measure does not distinguish whether this is due to the sex ratio in the field, the size of the field or the strength of (corrected) assortative matching in the field.

Table 7: Instrumental variables estimates of the effects of degree completion on partnership formation and partner choice

	Men		Women	
	$\hat{\delta}$	s.e.	$\hat{\delta}$	s.e.
I. Medicine				
Partner	0.07***	(0.02)	−0.02	(0.02)
Partner university degree	0.07***	(0.03)	0.05**	(0.03)
Partner same field (uncorrected)	0.18***	(0.02)	0.12***	(0.02)
Partner same field (corrected)	0.13***	(0.03)	0.30***	(0.04)
Partner medical degree	0.21***	(0.02)	0.19***	(0.02)
II. Dentistry				
Partner	0.06	(0.06)	−0.04	(0.06)
Partner university degree	0.05	(0.08)	−0.02	(0.09)
Partner same field (uncorrected)	0.19***	(0.07)	0.04	(0.07)
Partner same field (corrected)	0.13	(0.10)	0.10	(0.15)
Partner dentistry degree	0.16***	(0.06)	0.17***	(0.06)
III. Veterinary medicine				
Partner	0.09*	(0.05)	−0.04	(0.04)
Partner university degree	0.12	(0.07)	0.03	(0.05)
Partner same field (uncorrected)	0.26***	(0.06)	0.08**	(0.04)
Partner same field (corrected)	0.34***	(0.09)	0.13***	(0.05)
Partner veterinary medicine degree	0.31***	(0.05)	0.18***	(0.03)
IV. International Business				
Partner	−0.02	(0.02)	0.04	(0.03)
Partner university degree	0.05	(0.03)	0.08*	(0.04)
Partner same field (uncorrected)	0.03	(0.02)	0.10***	(0.03)
Partner same field (corrected)	−0.05	(0.04)	0.02	(0.04)
Partner international business degree	0.07***	(0.01)	0.14***	(0.02)

Notes: All specifications include controls for ethnicity, age at the first lottery application, lottery category, year of first lottery, interaction terms of the year of first lottery and lottery category, and dummy variables for the year when the outcome is observed. "Partner same field" is a dummy variable rescaled using the transformation proposed by Liu and Lu (2006).
Levels of statistical significance: * p<0.10, ** p<0.05, *** p<0.01

Third, both male and female lottery winners are more likely to be in a partnership with someone who obtained a degree in the same lottery study program compared with non-admitted applicants. The effects tend to be larger than those we found for having a partner from the same field as lottery winners are more likely to meet (more) graduates from the lottery study program than the losers. The estimates are largest for veterinarians and doctors and somewhat smaller, but still substantial for dentists. The effects are smallest for international business, the program that is most similar to lottery losers' commonly chosen alternative study programs. We tend to find larger effects for the sex that is in the minority in the respective study program, while the effects are relatively similar for the gender-balanced field of dentistry.

The results indicate strong effects on assortative matching based on field of education and study program. The results are in line with Eika et al. (2019) who find substantial rates of assortative matching by college major in Norway. The graduates of our four lottery programs search to a larger extent for a partner within the social network of their study program or their profession than the lottery losers, which might be due to their preferences, meeting opportunities or labor market prospects. University and the workplace play a more important role as a marriage market for them than for the lottery losers in their second-best fields. The estimated effects might thereby be largest for medicine and veterinary medicine as the labor markets for these graduates likely bring about social and professional networks that are more homogeneous in terms of educational field than the networks of other college graduates.

Earnings returns

We now turn to estimates of the effect of completing a lottery study on the annual earnings of the applicants themselves, of their partners (conditional on having a partner) and their households. We focus on earnings at age 35, which is 15 to 17 years after their first lottery participation.[26]

For applicants' annual earnings, we estimate substantial returns to completing medicine for both male and female doctors (Table 8). The returns to a dentistry degree are even larger amounting to more than €62,000 for men and almost €40,000 for women. Completing international business or veterinary medicine does not significantly increase earnings for men. Female international business graduates earn almost €5,000 more than the lottery losers, while female veterinary medicine graduates earn almost €5,000 less than the lottery losers.

[26] The effects on earnings of applicants for medicine and dentistry for up to 22 years after the first lottery are explored in detail in Ketel et al. (2016) and Ketel et al. (2019).

Table 8: Instrumental variables estimates of the effects of degree completion on annual individual, partner and household earnings

	Men		Women	
	$\hat{\delta}$	s.e.	$\hat{\delta}$	s.e.
I. Medicine				
Earnings	33,050***	(2938)	29,138***	(1879)
Partner earnings	-2940*	(1787)	12,040***	(3547)
Household earnings	33,993***	(3471)	39,037***	(3766)
II. Dentistry				
Earnings	62,286***	(10,931)	39,660***	(8148)
Partner earnings	537	(6568)	3972	(10,958)
Household earnings	66,805***	(12,888)	40,698***	(13,364)
III. Veterinary medicine				
Earnings	7547	(6242)	-4889**	(2454)
Partner earnings	-2995	(4029)	7578*	(4096)
Household earnings	7963	(7739)	-1319	(4715)
IV. International Business				
Earnings	1,407	(3856)	4731*	(2844)
Partner earnings	-1540	(1963)	-547	(5715)
Household earnings	-421	(4506)	7638	(6174)

Notes: All specifications include controls for ethnicity, age at the first lottery application, lottery category, year of first lottery, interaction terms of the year of first lottery and lottery category, and dummy variables for the year when the outcome is observed.
Levels of statistical significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$

The earnings differences between partners of male doctors and non-doctors are negative, while female doctors have partners who earn significantly more than the partners of female non-doctors. This is likely in part due to the high degree of assortative matching that we found above as many female doctors have a partner with a medical degree. While we also found a high rate of assortative matching for male doctors, the negative earnings estimate for their partners might suggest that they are more likely to work fewer hours or stay at home - potentially even if they are a doctor themselves. This seems to be confirmed by the fact that the partners of male doctors are on average five percentage points more likely to have no income in the year the applicant is aged 35 compared to lottery losers' partners. Female dentists also more often have a partner who works as dentist, but the earnings differences relative to partners of non-admitted applicants for dentistry are imprecisely estimated and not statistically different from zero. While the partners of male veterinarians earn insignificantly less than the partners of lottery losers, the partners of female veterinarians earn about 7,600 euros more per year than their counterparts. Completing international business does not lead to earnings returns in the form of higher partner income.

Finally, we estimate the effects of degree completion on household earnings when the applicants are aged 35. The household earnings[27] returns are qualitatively similar to the individual returns. Both male and female doctors' households reap substantial returns to completing medicine, but the returns are now considerably larger for women which may again be driven by their higher propensity to be in a partnership with another doctor. The returns for dentists are higher than those for doctors amounting to almost €67,000 per year for men and €41,000 for women. The negative returns for female veterinarians and the positive returns for their partners roughly offset each other, so that there are no significant differences in household earnings relative to lottery losers. There are no significant household earnings returns for male veterinarians and for international business graduates.

Effects on fertility

Table 9 reports estimates of the effects of degree completion on the total number of children at age 35. Male doctors have on average more children at that age than male non-doctors. This effect could be driven by their higher probability to have a partner at that age, their higher earnings and/or their partner's somewhat lower labor force participation. For female doctors we do not find significant differences in the average number of children. The gender differences for doctors may reflect the greater difficulty of women to combine family and work in comparison to their male colleagues. For graduates from the other three programs, there are no significant differences in fertility in comparison to non-admitted applicants. For male dentists and male veterinarians the point estimates are, however, quite similar to those of male doctors.[28] While there

[27] Household earnings are computed as the sum of individual and partner earnings, but amount to individual earnings if the lottery applicant does not have a partner.

[28] Table 18 in the Appendix shows the effects on the probability to have at least one child by age 35. There are again only positive effects for male doctors, but none for the remaining graduates.

may be a positive earnings effect for male doctors on their number of children, such an effect does not seem to exist for dentists (or only to a lower degree) even though their earnings returns are markedly higher. Graduates' preferences for children and family life seem to play a more important role in their fertility decisions than their earnings.

Table 9: Instrumental variables estimates of the effects of degree completion on the number of children

	Men		Women	
	$\hat{\delta}$	s.e.	$\hat{\delta}$	s.e.
I. Medicine	0.36***	(0.06)	0.06	(0.05)
II. Dentistry	0.23	(0.17)	0.21	(0.18)
III. Veterinary medicine	0.21	(0.16)	0.01	(0.10)
IV. International Business	−0.06	(0.07)	0.002	(0.09)

Notes: All specifications include controls for ethnicity, age at the first lottery application, lottery category, year of first lottery, interaction terms of the year of first lottery and lottery category, and dummy variables for the year when the outcome is observed.
Levels of statistical significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Intergenerational effects

Finally, we report the estimates of the effect of completing medicine, dentistry, veterinary medicine or international business on the probability that the applicants' children enroll in the highest track of secondary education. In the Netherlands, primary school education comprises eight years and begins when children are four years old. After that, they are tracked into one of three secondary education tracks: pre-vocational education, senior general secondary education and pre-university education. Selection is based on teacher recommendations and on national standardized exams that students take in the final year of primary school, i.e. at age 11/12. On average, about 20% of all students are admitted to the pre-university track.

To assess the selectivity into the estimation samples of children that we use below, we first estimate the effect of degree completion on the probability of having at least one child who is at an age where students typically enter secondary school, both conditional and unconditional on having children (Table 19 in the appendix). Unconditional on having children, there are no significant differences between female lottery winners and losers, while male doctors, dentists and veterinarians are more likely to have a child who is at an age of having entered secondary education. Conditional on having children, female dentists and veterinarians are also more likely to have a child at an age of having entered secondary education. In line with the insignificant effects on fertility outcomes of international business graduates, there is no indication of selectivity into the sample of children for this program.

Children of male doctors are 7.7 percentage points more likely to enroll in the pre-university track than children of non-admitted applicants (Table 10). There are no differences in enrollment rates for children of female medicine lottery applicants or of dentistry applicants. The effects on children of applicants for veterinary medicine and international business studies are insignificant when the father was the applicant and significantly positive when the mother was the applicant. For male medicine and female international business graduates we found a 7 and 8 percentage point higher probability to have a partner with a university degree, respectively, which might partly explain the positive effects on children's school performance here. The effect size of around 9 percentage points is large relative to the baseline enrollment rates in the academic track of around 50%.

Table 10: Instrumental variables estimates of the effects of degree completion on children's academic enrollment

	Men			**Women**		
	$\hat{\delta}$	s.e.	N	$\hat{\delta}$	s.e.	N
I. Medicine	0.077**	(0.031)	5887	−0.003	(0.026)	9739
II. Dentistry	−0.031	(0.161)	277	−0.029	(0.118)	313
III. Veterinary medicine	0.039	(0.077)	723	0.091*	(0.053)	1289
IV. International business	−0.025	(0.027)	5640	0.098***	(0.035)	2957

Notes: All specifications include controls for ethnicity, age at the first lottery application, lottery category, year of first lottery, interaction terms of the year of first lottery and lottery category, child's gender, child's age of enrollment in secondary education, and dummy variables for year of secondary school enrollment. Levels of statistical significance: * p<0.10, ** p<0.05, *** p<0.01

2.7 Returns to medicine by second-best field of study

The counterfactual to completing each of the lottery fields is the second-best field which the lottery losers chose. As Table 4 shows, the second-best fields are diverse, which makes it likely that the effects vary by second-best field. In this section, we take a closer look at the effects of completing medicine in comparison to several second-best fields of study.[29] This provides additional insights into how these alternative fields are related to the family outcomes we consider.

The pairwise comparison of studies would be straightforward if the second-best field of study of each applicant was known. Since this is not the case for applicants who won the lottery and enroll in medicine, we use a procedure along the lines of Imbens and Rubin (1997).

We first divide all applicants into cells k based on their lottery category, lottery year and gender. Separately for each of the resulting 95 cells[30], we run IV-regressions of the outcome variables on the exogenous regressors (age at first application, non-western origin) and on the completion dummy using the result of the first lottery as instrument. For each cell, we store both the coefficient of the completion indicator ($\hat{\delta}_k$) and the variance of this estimate ($\hat{\sigma}^2_k$). Subsequently, we group the lottery losers' university degrees into four broad fields: 1) Health, 2) Social sciences (excl. Economics), Education, Humanities, Arts, Services (henceforth Social Sciences), 3) Business, Law and Economics (BALawEcon), and 4) Science, Mathematics, Informatics, Engineering, Manufacturing, Construction, Agriculture and Veterinary (STEM).

We slightly adapt the procedure that was developed by Imbens and Rubin (1997) to estimate outcome distributions of compliers in IV models and use it to estimate the fraction of compliers studying each of the four second-best fields we defined. We cannot identify compliers directly from the data, but can identify winning never takers (i.e. $LR_{i1} = 1$ and $C_i = 0$), and losing never takers and compliers combined (i.e. $LR_{i1} = 0$ and $C_i = 0$). For both groups we observe their distribution of second-best study choices. We also know the population shares ϕ_a, ϕ_n and ϕ_c of always takers, never takers and

[29]We focus on medicine as this is the only field with a sufficient number of observations to perform this analysis.

[30]We consider 4 lottery categories (C-F), 12 lottery years (1988-1999) and men and women separately, so that we obtain 96 cells (4x12x2). Since one cell does not contain any lottery losers, we exclude it and end up with 95 cells.

compliers, respectively. With that information, we can estimate the distribution of second-best study choices SC of the losing compliers in our data set, i.e. the fraction of compliers in the four second-best fields in each cell:

$$\begin{aligned} P_c(SC|LR_{i1}=0, C_i=0) = & \frac{\phi_c+\phi_n}{\phi_c} f(SC|LR_{i1}=0, C_i=0) - \\ & \frac{\phi_n}{\phi_c} f(SC|LR_{i1}=1, C_i=0) \end{aligned} \tag{2.3}$$

Due to the randomization caused by the lottery, the distribution of losing compliers' second-best study choices is identical to the distribution of fields that winning compliers would have chosen. Keeping only one observation per cell k, we lastly regress the IV coefficients obtained above ($\hat{\delta}_k$) on the four variables indicating the fractions of compliers in the four second-best fields (ρ_c^{Health}, $\rho_c^{Social\ Sciences}$, $\rho_c^{BALawEcon}$, ρ_c^{STEM}) obtained in equation (2.3), on lottery category (Lcat), lottery year (Lyear) and a gender dummy.[31] Thereby, we use the precision (i.e. the inverse of the variance $\hat{\sigma}_k^2$) of the IV regression estimates as weights:

$$\begin{aligned} \hat{\delta}_k = & \beta_{Health}\, \rho_c^{Health} + \beta_{Social\ Sciences}\, \rho_c^{Social\ Sciences} + \beta_{BALawEcon}\, \rho_c^{BALawEcon} \\ & + \beta_{STEM}\, \rho_c^{STEM} + Lcat_k + Lyear_k + \delta female + U_k \end{aligned} \tag{2.4}$$

Table 11 reports results from this procedure for the probability to have a partner at age 35 and for partner characteristics. Each of the estimates can be interpreted as the effect for a specific complier group, for instance: the compliers who would have studied STEM if losing the first lottery for medicine.[32]

Although the coefficient estimates vary considerably by second-best field, hardly any of the effects are statistically significant. They do reveal some interesting patterns though. First, the coefficients suggest that doctors whose second-best field is STEM are less likely to have a partner than losing compliers, whereas doctors whose second-best field is Health, Social Sciences or BALawEcon are more likely to have a partner than losing compliers. Second, the effects on the probability to have a partner with a

[31] Contrary to the previous analyses, we do not split the sample by gender as it would further reduce the power of the regression model.

[32] Differences in the estimates within a column should not be understood as differences in causal effects between for example medicine vs. Social Sciences and medicine vs. STEM. The reason is that applicants with different second-best fields are likely to have different potential outcomes, as doctor but also in each of the alternative fields.

university degree are positive for Health, Social Sciences and STEM, but negative for BALawEcon. Third, completing medicine increases the probability to have a partner from the same field relative to graduates in Health, Social Sciences and STEM, while it decreases it relative to graduates in BALawEcon. Lastly, doctors are considerably more likely to have a partner with a medical degree than graduates in other health-related study programs. The effects in comparison to the remaining three fields are insignificant and of lower magnitude.

Table 11: Differences in partner choice at age 35 of medicine graduates by second-best field of study

	Partner	Partner university degree	Partner same field	Partner medical degree
Health	0.072	0.111	0.097	0.357***
	(0.138)	(0.187)	(0.170)	(0.153)
Social Sciences	0.027	0.010	0.044	0.174
	(0.146)	(0.163)	(0.192)	(0.172)
BALawEcon	0.077	−0.292	−0.100	0.033
	(0.183)	(0.254)	(0.233)	(0.208)
STEM	−0.023	0.042	0.152	0.189
	(0.111)	(0.156)	(0.146)	(0.129)

Notes: Standard errors in parentheses. Levels of statistical significance: * p<0.10, ** p<0.05, *** p<0.01

The differences in earnings and fertility at age 35 by second-best field are provided in Table 12. The earnings returns to medicine are highest for graduates whose alternative choice is another health-related program or in the broad field of Social Sciences. The returns to completing medicine in comparison to BALawEcon and STEM are considerably lower and not statistically significant. Partner's earnings are lower in comparison to all fields, but these differences are always insignificant. Household earnings differences follow a similar pattern as individual earnings differences, albeit only the returns relative to Health differ significantly from zero at the 10% level. The estimated differences in the number of children at age 35 are always positive, but are too imprecisely estimated to be of statistical significance. Nonetheless, the results suggest that the largest differences in fertility can be found between doctors and graduates in other health-related programs, Business, Law and Economics.

Overall the pattern arises that we find most effects for doctors whose second-best alternative is Health or Social Sciences, while the effects for doctors with a STEM field or BALawEcon as their second-best are all insignificant. A suggestive explanation for this is that both STEM and BALawEcon are more similar to medicine in terms of marriage market attractiveness (ability, social status and/or labor market potential) than Health (excluding medicine) and Social Sciences, a mechanism brought forward by Kaufmann et al. (2015).

Table 12: Differences in earnings and fertility outcomes at age 35 of medicine graduates by second-best field of study

	Earnings	Partner earnings	Household earnings	Number of children
Health	57,149***	-21,209	53,413*	0.652
	(20,233)	(15,821)	(28,972)	(0.405)
Social Sciences	60,885***	-16,584	52,794	0.149
	(19,969)	(20,267)	(31,921)	(0.433)
BALawEcon	31,455	-24,041	6191	0.473
	(25,103)	(21,443)	(38,267)	(0.539)
STEM	16,157	-1395	16,775	0.121
	(16,012)	(13,240)	(23,716)	(0.337)

Notes: Standard errors in parentheses. Levels of statistical significance: * p<0.10, ** p<0.05, *** p<0.01

2.8 Conclusion

This paper documents that family outcomes of university graduates differ substantially by their field of study. To deal with the self-selection of students into fields of study, we exploit admission lotteries for four substantially oversubscribed study programs. Our results show that lottery winners are more likely to have a partner from the lottery field than lottery losers. We interpret this as evidence that search frictions play a role on the marriage market. However, the lottery winners are also more likely to find a partner in their broad field of study than the lottery losers. This indicates that search frictions are not the only explanation, but that also preferences are important for explaining assortative matching on the marriage market. Our analysis does not allow to quantify the importance of the different channels, which would require to also consider that losing a lottery may make someone less attractive for desired partners.

The channels through which fields of study influence labor market outcomes and fertility are probably even more complex. Own earnings are likely to influence and to be influenced by partner earnings, and both potentially influence and are influenced by fertility decisions. Children's educational outcomes may be directly influenced by own and partner's field of study, but most likely also by labor market outcomes, parents' ages at birth and the presence of siblings.

While pinning down the exact channels through which field of study affects family outcomes is complicated, studies like ours show that not only labor market outcomes, but also important other dimensions of a person's life are causally influenced by field of study. This concurs with the expectations of the students in the work of Wiswall and Zafar (forthcoming), that their study choices will affect not only their career but also their family outcomes.

2.9 Appendix

2.9.1 Figures

Figure 5: Fields of study of men (top panel) and women (bottom panel) by birth cohort

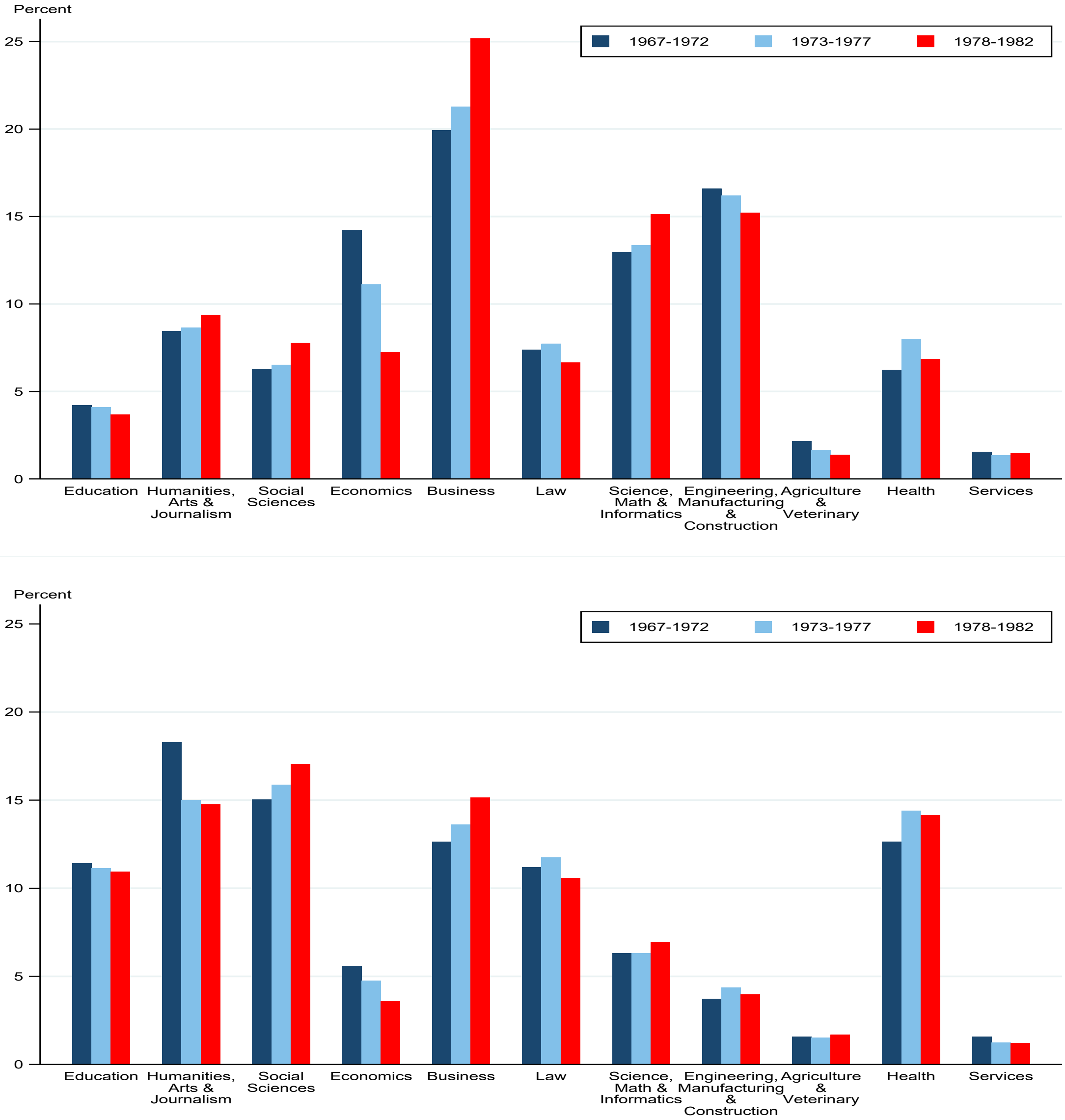


Figure 6: Probability to have a partner (top panel), be married (middle panel) and be divorced (bottom panel) by field of study

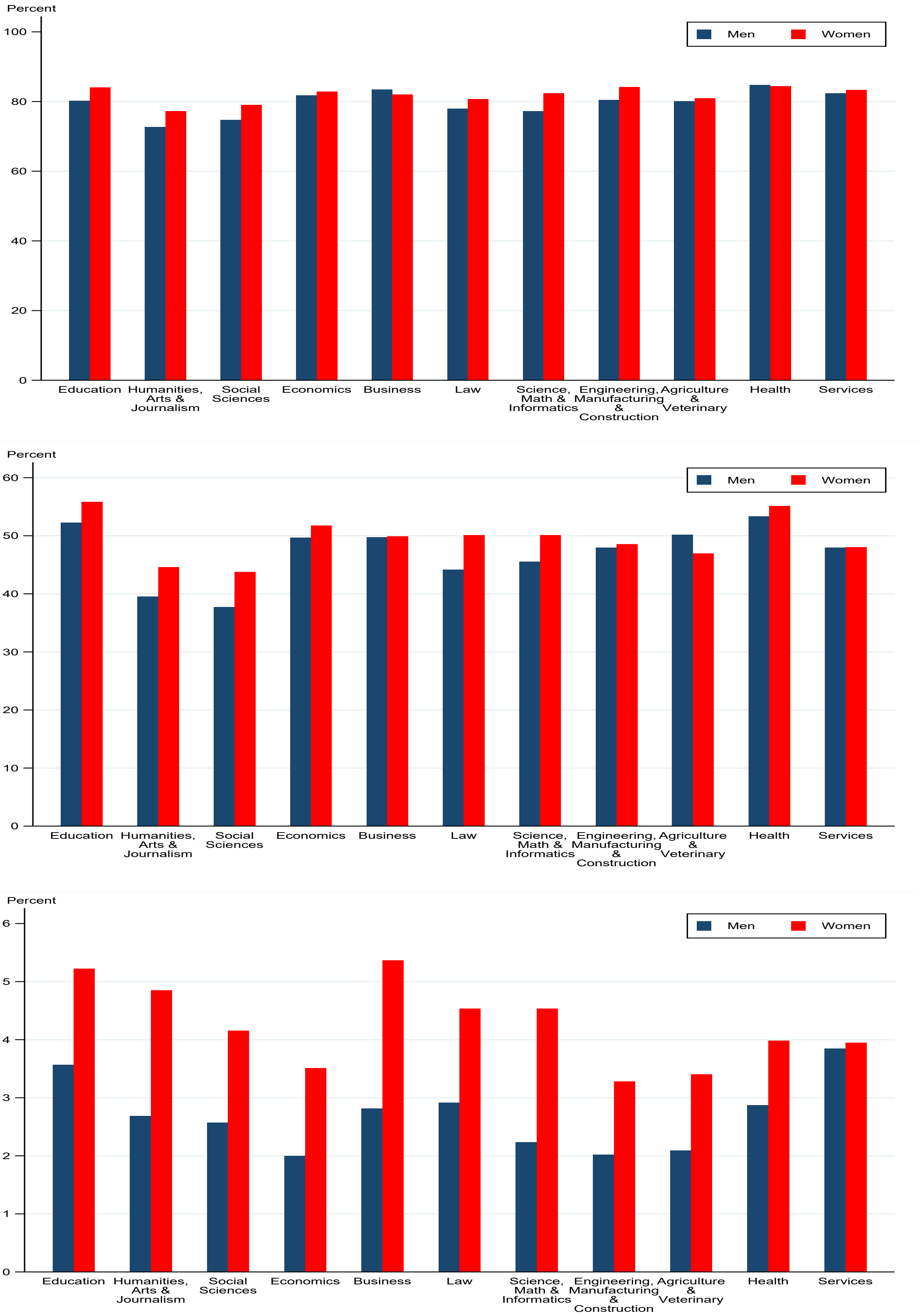
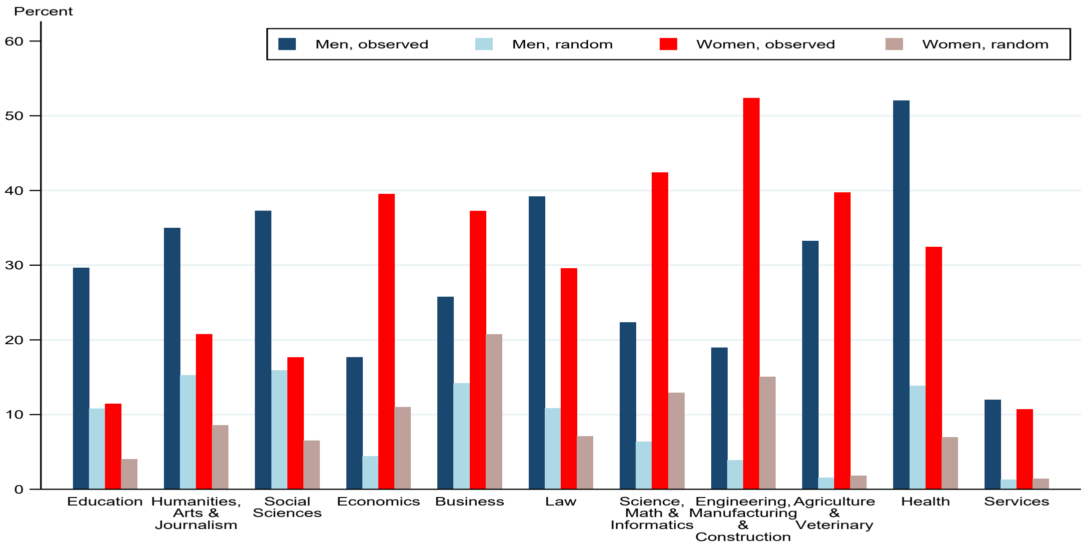


Figure 7: Assortative matching by field of study: Shares of graduates with a partner from the same field



2.9.2 Tables

Table 13: Balancing of individual characteristics by outcome of the first medicine lottery application

	Lottery winners	Lottery losers	p-value
Lottery category B			
Female	60.1%	61.1%	0.67
Age at first application	18.0	17.9	0.64
Non-Western immigrant	5.0%	4.1%	0.60
N	1805		
Lottery category C			
Female	62.2%	63.0%	0.43
Age at first application	18.0	18.0	0.18
Non-Western immigrant	4.2%	4.0%	0.50
N	2721		
Lottery category D			
Female	59.0%	59.5%	0.71
Age at first application	18.2	18.2	0.91
Non-Western immigrant	5.5%	5.5%	0.68
N	6069		
Lottery category E			
Female	57.4%	58.8%	0.25
Age at first application	18.4	18.3	0.71
Non-Western immigrant	7.7%	7.5%	0.31
N	6414		
Lottery category F			
Female	56.0%	56.2%	0.77
Age at first application	18.6	18.5	0.02
Non-Western immigrant	10.7%	10.4%	0.32
N	8384		

Notes: The p-values in the final column are weighted by the admittance probabilities for students in different years of lottery application.

Table 14: Balancing of individual characteristics by outcome of the first dentistry lottery application

	Lottery winners	Lottery losers	p-value
Lottery categories B & C			
Female	59.0%	55.6%	0.60
Age at first application	18.1	17.9	0.18
Non-Western immigrant	7.0%	6.7%	0.59
N	162		
Lottery category D			
Female	56.5%	54.9%	0.62
Age at first application	18.2	18.2	0.38
Non-Western immigrant	8.4%	7.2%	0.53
N	344		
Lottery category E			
Female	50.0%	49.0%	0.71
Age at first application	18.5	18.5	0.10
Non-Western immigrant	8.1%	6.6%	0.28
N	522		
Lottery category F			
Female	44.2%	50.4%	0.12
Age at first application	18.8	18.7	0.23
Non-Western immigrant	9.1%	12.1%	0.12
N	893		

Notes: The p-values in the final column are weighted by the admittance probabilities for students in different years of lottery application.

Table 15: Balancing of individual characteristics by outcome of the first veterinary medicine lottery application

	Lottery winners	Lottery losers	p-value
Lottery category B			
Female	69.9%	71.2%	0.91
Age at first application	17.9	17.8	0.27
N	139		
Lottery category C			
Female	65.8%	67.4%	0.77
Age at first application	18.1	18.0	0.09
N	307		
Lottery category D			
Female	61.8%	70.2%	0.03
Age at first application	18.2	18.3	0.08
Non-Western immigrant	1.2%	1.4%	0.98
N	839		
Lottery category E			
Female	69.4%	64.9%	0.16
Age at first application	18.5	18.4	0.49
Non-Western immigrant	3.7%	1.9%	0.08
N	1116		
Lottery category F			
Female	65.6%	65.9%	0.66
Age at first application	18.7	18.7	0.79
Non-Western immigrant	3.4%	1.8%	0.12
N	1508		

Notes: The p-values in the final column are weighted by the admittance probabilities for students in different years of lottery application. In compliance with the data privacy regulations of Statistics Netherlands, we do not report the fractions of non-western immigrants in categories B and C as they are too small.

Table 16: Balancing of individual characteristics by outcome of the first international business lottery application

	Lottery winners	Lottery losers	p-value
Lottery categories B & C			
Female	37.7%	37.3%	0.61
Age at first application	18.1	18.1	0.50
Non-Western immigrant	4.4%	2.5%	0.16
N	860		
Lottery category D			
Female	32.9%	34.0%	0.70
Age at first application	18.3	18.4	0.22
Non-Western immigrant	3.7%	2.6%	0.74
N	1765		
Lottery category E			
Female	31.5%	28.9%	0.20
Age at first application	18.6	18.6	0.60
Non-Western immigrant	5.6%	3.3%	0.02
N	2183		
Lottery category F			
Female	28.4%	29.3%	0.58
Age at first application	18.7	18.7	0.55
Non-Western immigrant	6.1%	5.3%	0.60
N	3172		

Notes: The p-values in the final column are weighted by the admittance probabilities for students in different years of lottery application.

Table 17: Instrumental variables estimates of the effects of degree completion on marital status

	Men		**Women**	
	$\hat{\delta}$	s.e.	$\hat{\delta}$	s.e.
I. Medicine				
Married	0.13***	(0.03)	0.002	(0.02)
Divorced	0.01	(0.01)	−0.0002	(0.01)
II. Dentistry				
Married	0.15*	(0.08)	−0.04	(0.08)
Divorced	0.02	(0.02)	0.004	(0.02)
III. Veterinary medicine				
Married	0.03	(0.07)	−0.10**	(0.04)
Divorced	0.003	(0.02)	0.03*	(0.01)
IV. International Business				
Married	0.03	(0.03)	−0.01	(0.04)
Divorced	−0.02	(0.01)	−0.03*	(0.01)

Notes: All specifications include controls for ethnicity, age at the first lottery application, lottery category, year of first lottery, interaction terms of the year of first lottery and lottery category, and dummy variables for the year when the outcome is observed.
Levels of statistical significance: * p<0.10, ** p<0.05, *** p<0.01

Table 18: Instrumental variables estimates of the effects of degree completion on the probability to have a first child

	Men		**Women**	
	$\hat{\delta}$	s.e.	$\hat{\delta}$	s.e.
I. Medicine	0.13***	(0.03)	0.03	(0.02)
II. Dentistry	0.11	(0.08)	0.02	(0.07)
III. Veterinary medicine	0.11	(0.07)	−0.01	(0.04)
IV. International Business	−0.004	(0.03)	0.01	(0.04)

Notes: All specifications include controls for ethnicity, age at the first lottery application, lottery category, year of first lottery, interaction terms of the year of first lottery and lottery category, and dummy variables for the year when the outcome is observed.
Levels of statistical significance: * p<0.10, ** p<0.05, *** p<0.01

Table 19: Instrumental variables estimates of the effects of degree completion on sample selectivity

	Men		Women	
	$\hat{\delta}$	s.e.	$\hat{\delta}$	s.e.
I. Medicine				
Unconditional on having children	0.111***	(0.021)	0.028	(0.020)
Conditional on having children	0.092***	(0.023)	0.0002	(0.021)
II. Dentistry				
Unconditional on having children	0.186***	(0.062)	0.098	(0.062)
Conditional on having children	0.208***	(0.075)	0.135*	(0.073)
III. Veterinary medicine				
Unconditional on having children	0.102*	(0.059)	0.008	(0.037)
Conditional on having children	0.125*	(0.068)	0.079**	(0.040)
IV. International business				
Unconditional on having children	−0.029	(0.031)	0.014	(0.039)
Conditional on having children	0.008	(0.027)	−0.003	(0.030)

Notes: All specifications include controls for ethnicity, age at the first lottery application, lottery category, year of first lottery, and interaction terms of the year of first lottery and lottery category.
Levels of statistical significance: * p<0.10, ** p<0.05, *** p<0.01

CHAPTER 3

Household specialization and the child penalty in the Netherlands[33]

3.1 Introduction

A recent literature shows that first-time parenthood has substantial and persistent negative effects on women's labor market outcomes, while it has only minor negative effects for men (Bütikofer et al., 2018; Chung et al., 2017; Kleven et al., 2019*a*,*b*; Sieppi and Pehkonen, 2019).[34] Inspired by Becker (1985) it has been hypothesized that household specialization based on comparative advantage is an important channel for this so-called child penalty for women.[35] The evidence regarding this channel is, however, mixed. Angelov et al. (2016), Pora and Wilner (2019) and Chung et al. (2017) find support for it[36], while Andresen and Nix (2019), Kleven et al. (forthcoming) and Rosenbaum (2019) do not.

[33]This chapter is joint work with Hessel Oosterbeek and Bas van der Klaauw.

[34]These papers conduct event studies centered around the birth of the first child to estimate the effect of parenthood on labor market outcomes of mothers compared to fathers. A different approach is used by Lundborg et al. (2017) who exploit IVF-treatments in Sweden to obtain exogenous variation in fertility among childless women to estimate the causal effect of having children on their career. Their findings concur with the results of the papers that use an event-study design.

[35]Other mechanisms discussed in the literature are biology, preferences and gender norms (cf. Andresen and Nix, 2019).

[36]Angelov et al. (2016) find that the magnitude of the within-couple earnings gap depends on the relative earnings within the family. Relating the child penalty to women's pre-childbirth rank in the distribution of hourly wages, Pora and Wilner (2019) conclude that child penalties arise from decisions

A possible reason for the mixed evidence is that the importance of the household specialization channel varies across settings due to differences in relevant institutions regarding for example the possibilities to adjust working hours or to use formal child care for very young children. In this paper, we investigate the importance of household specialization in a setting – the Netherlands – where there are arguably no institutional hurdles to divide household tasks in a gender-neutral way. In the Netherlands, employees are legally entitled to unilaterally change the working hours of their already existing contract. This is one of the reasons why not only the share of part-time working women is very high, but also the fraction of men working less than 30 hours per week is with 19.4% in 2019 by far the highest among all OECD countries (OECD, 2020*d*). It is therefore easier and presumably more accepted for fathers to trade market work for child care if their partner has better earnings prospects. Furthermore, formal child care is available for children as young as three months so that parents have the option to use it when paid maternity leave ends (Plantenga and Remery, 2009).

Using the event-study approach proposed by Kleven et al. (2019*a*), we first replicate results from other countries; there are large and persistent negative effects of first parenthood on women's earnings, while there is no effect on men's earnings. The earnings child penalty is about 47% ten years after women have their first child. This is mostly due to a reduction in working hours right after childbirth and to a lesser degree to lower participation and a gradual decrease in wage rates. Conducting the analysis by parents' level of education, we find a similar earnings child penalty for college and non-college educated women though its drivers differ. We also find substantial, but heterogeneous child penalties for all fields of study, whereby the child penalty is lowest in the male-dominated fields of Science and Mathematics, and Informatics.

To study whether couples divide household and market work based on comparative advantages and bargaining power, we construct various measures of mothers' and fathers' earnings potential. The measures differ in how sophisticated they assume households to be. Using different measures of relative earnings potential will give more insights into the factors that couples take into account when bargaining over childcare and market work. While all our proxies for relative earnings potential measure

based on specialization gains rather than on preferences or gender norms. Chung et al. (2017) find that the within-couple earnings gap increases more for couples where the male spouse has a higher education than the female partner.

different aspects of earnings capacity, overall we find little evidence of household specialization based on comparative advantages. Women with higher within-household earnings capacity reduce their labor supply less than women with lower relative earnings potential, but men only marginally adjust their labor supply after childbirth irrespective of their relative earnings potential. We therefore conclude that even in a setting that is conducive for young parents to divide household tasks in a gender-neutral way, spouses do not specialize according to their comparative advantage. Descriptive evidence instead suggests that the use of formal child care is more sensitive to women's earnings potential implying that higher-earning/higher-educated women pay for more child care to reconcile work and family.

Apart from the recent literature on the child penalty, our paper relates to the literature on the effects of first-time parenthood on women's labor supply and earnings more generally (see e.g. Adda et al., 2017; Bertrand et al., 2010; Hotz et al., 2017; Lundberg and Rose, 2000; Lundborg et al., 2017; Paull, 2008; Waldfogel, 1998; Wilde et al., 2010). Our paper also relates to the vast literature on gender inequality in the labor market with recent reviews by Blau and Kahn (2017) and Olivetti and Petrongolo (2016). This literature among others finds that traditional human capital variables contribute little to the gender gap in recent years, but that gender differences in occupation and industry, career interruptions, shorter working hours and the unequal gender division of labor continue to play important roles.

The remainder of the paper is structured as follows. Section 3.2 provides a brief overview of the institutional background in the Netherlands. Section 3.3 describes our data and empirical approach. Section 3.4 discusses our proxies for earnings potential and presents our findings, and section 3.5 concludes.

3.2 Institutional background

Female labor force participation expanded considerably later in the Netherlands than in other OECD countries. For most of the 1980s, women's employment rate was around 30%, while it was, for instance, above 70% in Sweden (OECD, 1989). This changed in the 1990s when the female employment rate increased rapidly to 63.5% in 2000. With 74% in 2019, it is now among the highest of all OECD countries (OECD, 2020*b*). However, many women in employment work on a part-time basis. While working reduced hours was already very common in the 1990s, access to part-time work was further facilitated by the Adjustment of Working Hours Act (Wet Aanpassing Arbeidsduur, WAA) that came into force in June 2000. This law mandated that under certain conditions employees are entitled to a change in the working hours of their already existing contract (Wilthagen et al., 2004). In 2019, about 56.9% of women worked less than 30 hours a week, while the average in the OECD is 25.4%. Among men, this fraction is with 19.4% about twice as high as the OECD average of 9.6%, making it the highest part-time working rate of men among all OECD countries. During the period we observe labor market outcomes (1999-2018), between 55.4% and 61.1% of women and between 11.9% and 19.2% of men were working less than 30 hours per week (OECD, 2020*d*).

The Dutch social security and pension system insures individuals against income losses in case of divorce, end of a registered partnership or death of one partner. If one spouse or registered partner dies, the other is entitled to a survivor's pension (Rijksoverheid, 2020*a*). Unless explicitly agreed otherwise in the divorce/separation settlement, both spouses are entitled to an equal share of any pension built up during the marriage/registered partnership (pension equalisation, 'pensioenverevening'). If the ex-partner dies before reaching the pensionable age, the other partner may also be entitled to a survivor's pension ('nabestaandenpensioen'). Further, parents are obliged to pay child maintenance until the child turns 21 in case of a divorce or separation (Rijksoverheid, 2020*b*). These rights and obligations apply equally to men and women.

Fertility rates decreased considerably in the 1960s and 1970s before leveling off at around 1.6 children per woman. In the 2000s, fertility rose again to about 1.7 to 1.8 children per woman during our observation period (first births between 2004 and 2013), though subsequently dropped again to 1.6 in 2018. Women's average age when having their first child increased gradually from 28 years in 1992 to 30 years in 2018 (Eurostat, 2020).

During our observation period, parents were initially subject to the 2001 Work and Care Act regarding leave regulations (Plantenga and Remery, 2009). It stipulated women's entitlement to 16 weeks of paid maternity leave, with four to six weeks taken before the expected birth of the child and the remainder thereafter. Fathers were entitled to two days of paid paternity leave ('kraamverlof'), which had to be taken within four weeks after the birth of the baby. The Act also included the right to primarily unpaid parental leave for a maximum of 13 times the contractual weekly working hours taken on a part-time (50%) basis until the child turns eight. This right is granted to both mothers and fathers and is not transferable. The law was designed to enable the reconciliation of (part-time) work and family and to foster a more gender-equal division of paid and unpaid work (Plantenga and Remery, 2009). It required financial compensation for parental leave only for public-sector employees, while other workers had to negotiate compensation in their collective agreements. Consequently, only a minority of employed parents obtained 13 weeks of paid parental leave (Knijn and Saraceno, 2010). In January 2009, the parental leave period was extended from 13 to 26 weeks on a half-time basis (Plantenga and Remery, 2009).

Formal child care has been expanded substantially since the late 1990s with the goal to foster the reconciliation of market and family work, while potential educational benefits of child care have not been the focus (Knijn and Saraceno, 2010). It is also available for very young children so that parents can make use of it when paid maternity leave ends (Plantenga and Remery, 2009). The costs for child care are shared by the government, employers and parents, whereby the individual contributions of the three parties have changed over time. Under certain conditions, for instance if both partners are working, parents are entitled to income-dependent child care subsidies. However, even with subsidies, costs for child care can be high. Since the 2005 Dutch Act on Child Care, part of the child care costs can be deducted from income tax. Since 1 January 2007, employers are mandated to pay one sixth of the costs for child care per parent (Knijn and Saraceno, 2010). Most children attend child care facilities only part of the week as the vast majority of mothers works part-time. Children typically enter primary school at age four, though the first year of school is not mandatory. In 2008, primary schools have been mandated to either offer full-day childcare or to offer facilities for out-of-school care for children aged four to twelve (Knijn and Saraceno, 2010).

3.3 Data and empirical strategy

This section describes the data used in the empirical analysis, provides summary statistics of the data and explains our empirical approach.

3.3.1 Data sources and sample

We use administrative data from different registers available at Statistics Netherlands (CBS). We use the registers on spouses/registered partners and on cohabiting partners to link couples, and the register that links children to their parents to identify first-time births. Information on individuals' level and field of education is drawn from the records on educational attainment. Our data on labor market outcomes comprises annual working hours for the employed population (2006-2018), earnings from employment (1999-2018), earnings from self-employment (1999-2018), income from abroad (2001-2018) and income from other sources of labor (2001-2018). Total annual income is computed as the sum of before-tax income from these four sources and is converted to 2015 euros. We infer wage rates as annual income from employment divided by annual working hours.

Earnings are top-coded at 200,000 euro, annual hours at the legal limit of 2496 hours (48 hours per week) and wage rates are top-coded at 1000 euro. We also bottom-code negative income from self-employment at -200,000 euro and drop observations with imputed wage rates lower than 2 euro. Our indicator for labor force participation is set to 1 if an individual's total annual earnings are at least 50% of the amount that a couple would receive in welfare benefits. The welfare benefit level for couples is set at 100% of the net minimum wage. The gross minimum wage amounted to 1501.80 euro per month at the beginning of 2015, which in net is about 1300 euro although this depends on personal circumstances. Participation thus equals one if annual earnings amount to at least 7800 (650×12) euro in 2015. Since the minimum wage is roughly raised with the inflation rate (twice per year), we will inflation-adjust this amount to determine the minimum earnings threshold for the years 1999 to 2014 and 2016 to 2018.[37]

We also use data on the use of formal child care that is eligible for subsidies by the government (2007-2018). It comprises information on parents' annual costs for child care as well as the number of hours that a child spent in formal care in a year. Households that did not qualify for child care subsidies, e.g. because one of the partners was not working in a year, are not included in the data set. Costs and hours of child care

[37] We obtain quantitatively similar results if we do not re-code earnings and working hours. If we do not impose a minimum earnings threshold for the participation indicator, then the post-birth drop in women's participation rate and the long-term child penalty are smaller.

are set to zero for these households. We will not use the available information on child care subsidies as the latter are income dependent.

Our sample of individuals comprises mothers and fathers who had their first child between 2004 and 2013 and were observed in the CBS registry in the year before the birth of their first child. We further restrict the analysis to men and women who were between 24 and 44 years old when having their first child to exclude most individuals who gave birth while still in education. The lower bound eliminates about 11.9% of mothers and 4.3% of fathers, while the upper bound eliminates about 0.1% of mothers and 2% of fathers. We do not impose restrictions on the relationship status of the parents in our separate analysis of mothers and fathers. This means we also include a parent if the other parent is unknown in the CBS-registry. We use an unbalanced sample of individuals to obtain estimates for five years before and 10 years after having a child.

For our analysis of households, we additionally impose that both parents were aged 24 to 44 when having their first child and that both were observed in the CBS registry in the year prior to childbirth. We also require that the parents were married and/or cohabiting in the year when their first child is born and that the first joint child of the parents is also the first child for both partners individually.

3.3.2 Descriptive statistics

Table 20 shows summary statistics for our full sample of more than 700,000 mothers and fathers and for the more than 600,000 women and men in our household sample. Men are about two years older than women when their first child is born. Women are more likely to have a college degree than men, albeit information on highest educational attainment is missing for about 22.3% of women and 28.5% of men. This fraction is higher for men as they tend to be older than their female partners and the coverage of educational attainment in the CBS registries declines with age.[38] The fraction of college graduates is slightly larger in the household sample and labor market outcomes in the year before birth are also slightly more favorable for the latter group. Women earn more than 10,000 euros less than men in the year before birth. Average working hours are almost 300 hours lower among women compared to men and hourly wages for

[38] CBS's coverage of college graduation records is also more comprehensive than that of other levels of education, so that a large part of the individuals with missing education information likely has no college degree.

women are also considerably lower than male wages. Female labor force participation falls about 4 percentage points short of male participation prior to birth. We observe individuals on average for 14.2 out of a maximum of 16 years.

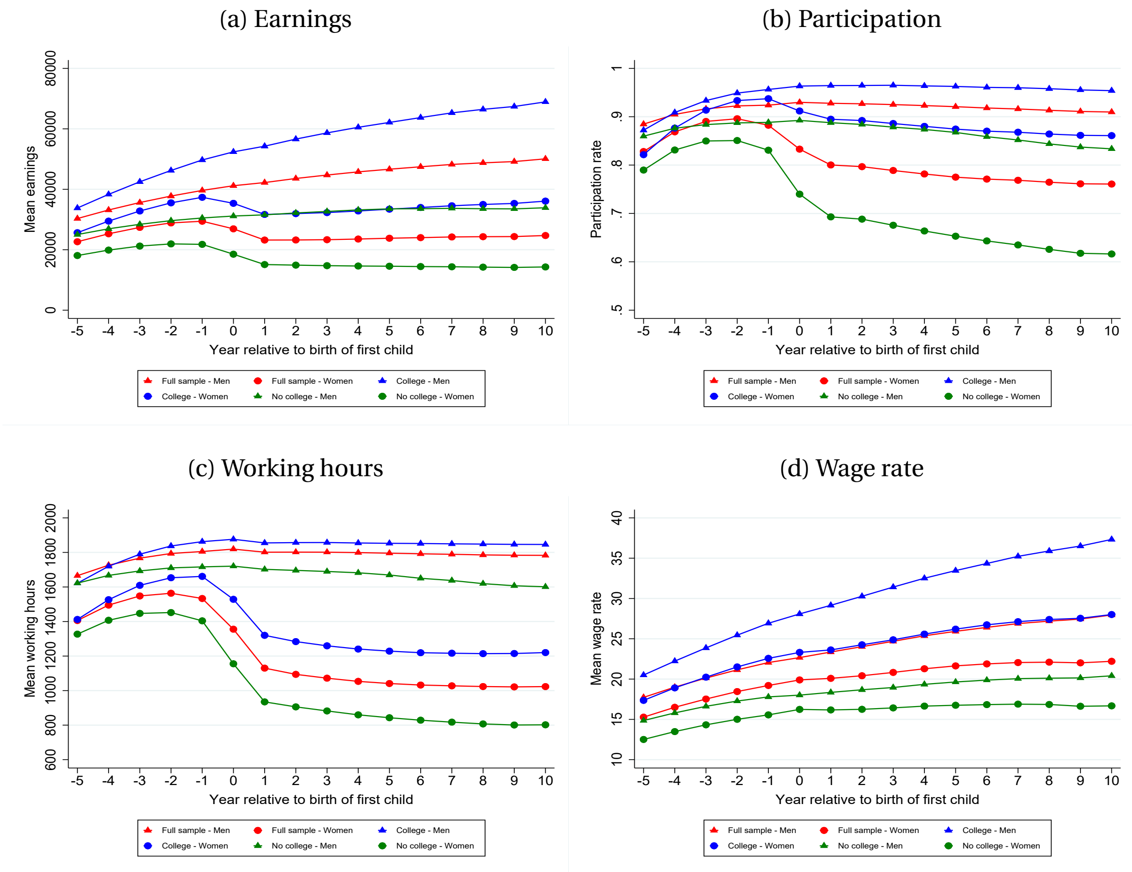
Table 20: Descriptive statistics by gender for the full and household sample

	Full sample		Households	
	Women	Men	Women	Men
Age at first birth	30.5	32.3	30.3	32.6
College degree	41.8%	34.9%	43.6%	38.5%
No college degree	35.9%	36.6%	33.9%	33.0%
Education unknown	22.3%	28.5%	22.5%	28.5%
Earnings in year before birth	29,427	39,619	30,268	41,826
Working hours in year before birth	1533	1805	1583	1866
Participation rate in year before birth	88.2%	92.4%	90.7%	94.7%
Wage rate in year before birth	19.2	22.1	19.2	22.7
Average number of years in data	14.2	14.2	14.2	14.3
N	714,329	724,949	601,644	601,644

Figure 8 depicts the development of average earnings, participation, working hours and wage rates over our 16-year observation period for the full sample and separately for college and non-college educated individuals by gender. Even though women's earnings are lower than men's in each (sub-)sample, they initially develop in parallel before diverging slightly in the year before birth. In the year of and one year after birth, women's earnings drop sharply and rise only slightly thereafter. There is no trend break around parenthood noticeable for men's earnings. Participation rates increase before birth, but women's participation decreases considerably after childbirth without recovery, while men's participation rates decline only marginally over time. A similar picture arises for working hours. In contrast, women's wage rates drop only slightly after childbirth and mostly seem to flatten off thereafter, whereas men continue on their pre-birth growth trajectories.

Table 21 presents descriptive statistics for the 601,644 households in our sample. About 26% of couples consist of two college graduates, while in 17% of households neither partner has a tertiary degree. In 9.7% of partnerships only the mother has a college degree and in 7.2% of households only the father. Educational information for

Figure 8: Average annual labor market outcomes relative to birth of first child



at least one partner is missing for almost 40% of our household sample. Average annual household earnings in the year before the first childbirth amount to about 72,000 euros, while total household working hours in employment average to 3226.

Table 21: Descriptive statistics on households as entities

Both college degree	26.2%
Both no college degree	17.0%
Only mother college degree	9.7%
Only father college degree	7.2%
Education of at least one partner unknown	39.9%
Household earnings in year before birth	72,094
Household working hours in year before birth	3226
N	601,644

Almost 73% of households use any formal child care that qualifies for government subsidies at some point between the year the first child is born and the year the child turns four. Average annual costs for formal care in that period amount to 4306 euro for an annual average of 711 hours spent in care. These figures include the use of child care for all children.

3.3.3 Empirical approach

To analyze the labor market effects of having the first child, we adopt the event-study methodology proposed by Kleven et al. (2019*a*,*b*). We construct an unbalanced panel of men and women and observe their labor market outcomes up to five years before and up to ten years after the birth of the first child. As the impact of parenthood differs by gender, we run this specification separately for men and women ($g = m, w$):

$$Y^g_{it\tau} = \alpha_g + \sum_{\tau=-5,\tau\neq-1}^{10} \delta^g_\tau D_\tau + \sum_j \beta^g_j A^g_{it\tau} + \gamma^g_t + U^g_{it\tau} \tag{3.1}$$

Outcome variables $Y^g_{it\tau}$ denote labor market outcomes (earnings, participation, working hours or wage rate) of individual i of gender g in year t and at event time τ. We measure all outcomes Y in levels, rather than in log, to keep zeros due to non-participation in the data set. The top-coding of outcome variables as described in section 3.3.1 mitigates the influence of extreme outliers on our results. Event times τ refer to the year relative to childbirth, with D_τ being indicator variables equal to one if the year of observation is (-5, ..., -2, 0, ..., 10) relative to the year of childbirth. We center the regressions around event time $\tau = -1$, so that our parameters of interest δ^g_τ measure the effect of having the first child relative to the last year before childbirth. Age dummies $A^g_{it\tau}$ control nonparametrically for underlying life-cycle trends, while γ^g_t are year dummies that control nonparametrically for time trends such as business cycles. Identification of these three sets of dummies is possible because there is enough variation in the timing of first child birth driven by variation in the age at which individuals enter parenthood.[39] Restricting the sample to individuals with children also eliminates any potential bias from selection into parenthood. We are thus not estimating gender differences in

[39]We do not include individual fixed effects as then not all sets of fixed effects in the model would be separately identified causing issues of multicollinearity.

the labor market effects of parenthood compared to not having children, but gender differences in labor market outcomes for those who have children.

With the estimates for the event-time coefficients $\hat{\delta}^g_\tau$ from equation 3.1, we compute the impact of children on men's and women's labor market outcomes in percentage terms. For that purpose, we calculate the year-τ effects of parenthood as a percentage of the counterfactual outcome of not having children:

$$P^g_\tau = \frac{\hat{\delta}^g_\tau}{E[\tilde{Y}^g_{it\tau}|\tau]} \tag{3.2}$$

The counterfactual $\tilde{Y}^g_{it\tau}$ is the predicted outcome when omitting the contribution of the event-time dummies in equation 3.1, i.e. $\tilde{Y}^g_{it\tau} = \hat{\alpha}_g + \sum_j \hat{\beta}^g_j A^g_{it\tau} + \hat{\gamma}^g_t$.

Lastly, we measure the child penalty on women relative to men at event time τ as follows:

$$P_\tau = \frac{\hat{\delta}^m_\tau - \hat{\delta}^w_\tau}{E[\tilde{Y}^w_{it\tau}|\tau]} \tag{3.3}$$

The child penalty gives the percentage by which women are falling behind men at event time τ due to parenthood. Since we are not restricting our sample to having only one child during our observation period, this measure will also include the effect of children born after the first one. We conduct this analysis for our full sample, by level of education (college vs. no college), by field of study and by various measures of within-household relative earnings potential explained in section 3.4.2 and in Appendix 3.6.3.

As common in event-studies, the identification of effects relies on the assumption that unobserved variables which determine labor market outcomes change smoothly over time. It also requires parallel trends, such that e.g. women (men) who had their first child in 2004 and women (men) who had their first child in 2013 would have had the same average annual changes in labor market outcomes in the absence of children. Further, trends for the outcome variables need to be parallel for men and women in the pre-treatment period in order to compare the effects for men and women and calculate long-run child penalties (Bütikofer et al., 2018).

Another important identifying assumption of the above methodology is the absence of anticipation effects, i.e. individuals' decision to have their first child is independent of expectations about future labor market developments. Yet, it is, for instance, conceivable that couples decide to have a child because the man was promised to receive a promotion in the future or because the woman was able to secure a move to a more family-friendly job in advance. We would then wrongly attribute the changes in labor market outcomes to parenthood, while they would have occurred even in the absence of children, thus violating the assumption of exogenous timing of parenthood (Albrecht et al., 2018; Angelov et al., 2016). In addition, individuals endogenously select into levels and fields of education, but also partnerships, based on ability, preferences for e.g. child care and career, workforce attachment, etc. We therefore interpret our estimates as correlational evidence instead of as causal effects.

An additional concern with this event-study approach is that with five years the pre-birth window is relatively short and comprises years where earnings tend to be unstable. The average age at first childbirth in our sample is around 30 years, so that the pre-birth observation period mostly covers individuals' mid- to late-twenties. At these ages, annual earnings are not a good approximation to lifetime earnings as transitory income shocks confound the measurement of permanent earnings (Haider and Solon, 2006; Nilsen et al., 2012). Yet, these earnings are used in the event-study approach to estimate counterfactual earnings trajectories and to calculate child penalties. If the age-dummies do not sufficiently control for these life-cycle trends, then the event-time dummies do not correctly capture the post-birth labor market adjustments of men and women.

3.4 Results

This section first shows the labor market trajectories around childbirth of our full sample of individuals as well as heterogeneity by level of education and field of study. It then describes our measures of relative earnings potential and presents findings indicating that households do not specialize based on comparative advantage. While men barely reduce their labor supply after childbirth irrespective of their relative earnings capacity, women with high relative earnings potential reduce their labor supply and hence earnings less than women with low within-household earnings potential. Finally, this section shows that a household's use of formal child care is more sensitive to women's earnings potential suggesting that high-earning women buy more child care to reconcile market work and family duties instead of relying on their partner.

3.4.1 Labor market trajectories of individuals

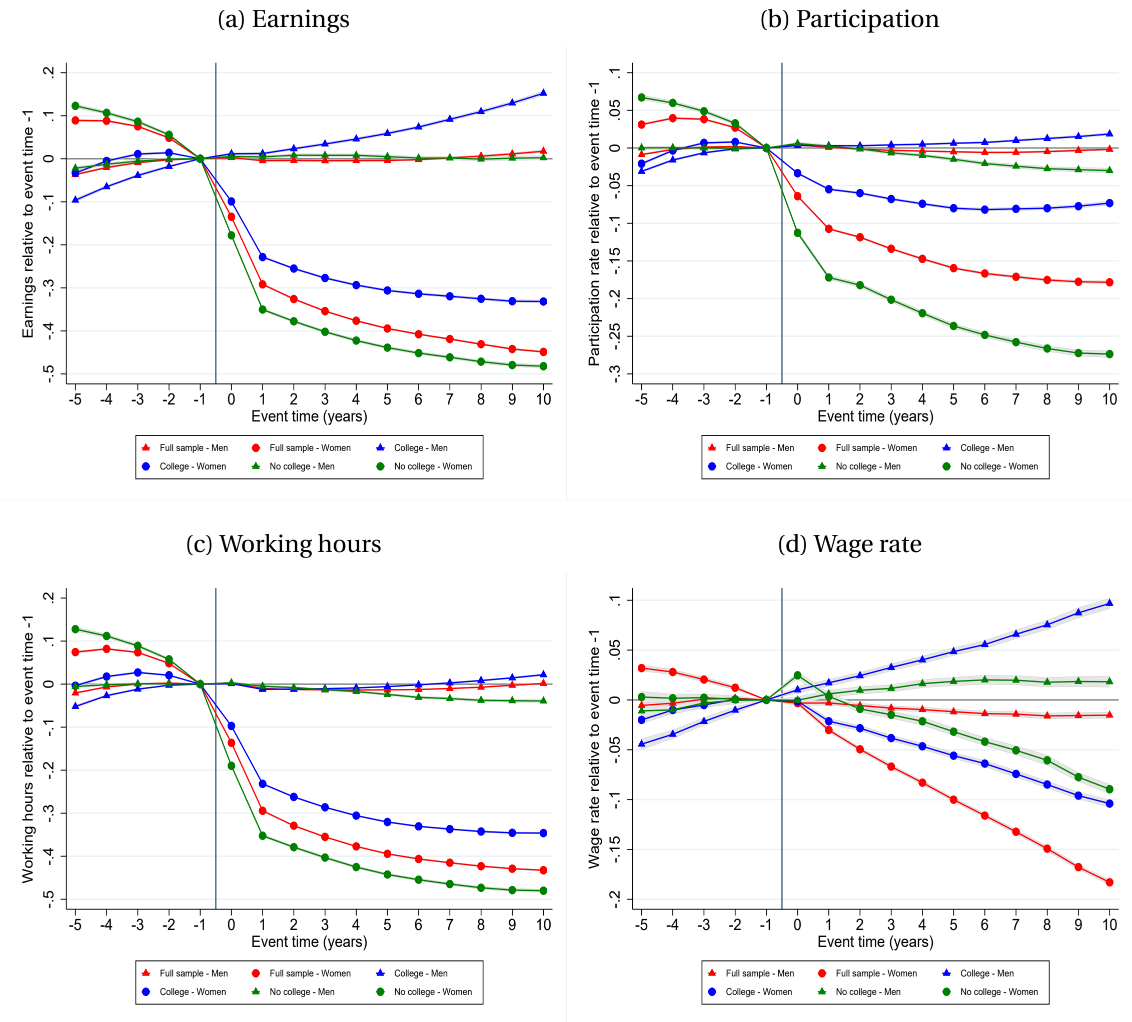
We first estimate the effects of parenthood on labor market outcomes of all men and women as well as separately by their level of education (college vs. no college).[40] Figure 9 plots the event-time coefficients as a fraction of the predicted counterfactual outcome, i.e. the gender-specific estimates P^g_τ. Women's earnings drop by about 13.5% in the year they give birth and by another 15.7% in the subsequent year compared to the year before birth. The earnings decline continues at a slower rate until women's earnings are almost 45% lower ten years after birth than they were just prior to parenthood. Noncollege-educated women face a larger earnings loss than mothers with a college degree. The earnings of men in the full sample and those without a college degree are unaffected by parenthood. College-educated men's earnings increase steadily and ten years after childbirth are 15% higher than in the year prior to parenthood. Despite the differing patterns for the three (sub-)samples, long-term child penalties are fairly similar amounting to 46.8% for all women, 50.0% for college-educated women and 48.5% for mothers without college degree (also see table 23).

To provide a better picture of the sources of the earnings child penalty, we now look at the three components of earnings, i.e. participation, working hours and wage rates. Women's participation rate drops in the year of childbirth and continues decreasing thereafter. The likelihood to leave the labor force is considerably larger for women without a college degree than for college-educated mothers. Men's decision to participate in the labor force is largely unaffected by having children. Overall, this results in long-term child penalties of 17.7% for all women, 9.2% for mothers with a college degree and 24.3% for lower educated women. Women's working hours decrease after parenthood at a rate that roughly mirrors their drop in earnings. Men's decrease in working hours is negligible and mostly short-lived. Only men without college education have somewhat lower working hours in the long run when compared to the year before childbirth. The long-term child penalties amount to around 43.5% for all and for noncollege-educated women, and to 36.7% for mothers with a college degree.

The wage rate trajectories differ from the pattern for earnings, participation and working hours. Women's wage rates decrease gradually after birth, whereby the reduc-

[40] The full sample also includes individuals for whom education is unknown (see table 20).

Figure 9: Labor market trajectories by level of education



Note: The figures show the estimated coefficients (with confidence intervals) of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child separately for men and women, i.e. P_τ^g (as defined in 3.2).

tion is slightly larger for college- than for noncollege-educated women.[41] In contrast, fathers with a college degree experience a continuous increase in their wage rate that by far surpasses the wage growth of noncollege-educated fathers. The child penalty is with 20.9% largest for college-educated women who seem to miss out on promotions and

[41] This is in line with Adda et al. (2017) who find the largest atrophy rates for women in abstract occupations, which on average require a higher level of education than routine and manual occupations.

pay raises while their male peers' hourly wages increase considerably. The child penalty on lower-educated women is 11.0%, while the penalty for all women amounts to 16.7%.

Overall, much of the earnings child penalty seems to be driven by women's large reduction in working hours and to a lesser extent by their decrease in participation. The gradual drop in women's wage rates gains in importance over time as a contributor to the penalty. Yet, we find significant pre-trends for all four outcomes that differ by gender within a (sub-)sample. In particular, women without a college degree show downward-sloping pre-trends for earnings, participation and working hours starting five years before the birth of the child, while there are either no or slightly upward-sloping pre-trends for noncollege-educated men. The pattern for women could be due to households that favor a more traditional division of labor where the woman already reduces her labor supply when getting married.[42] Such differences in pre-trends indicate that the parallel trends assumption required to measure the difference in the effects of parenthood on men and women may not hold. This also cautions us against interpreting the estimates as identifying causal effects.

The above results show differential effects of parenthood for college and noncollege-educated women whereby outcomes tend to be more favorable for the latter. Since fields of study differ substantially along a variety of dimensions such as skill requirements, curriculum, career opportunities and hence the student pool they attract, it is likely that the effects of parenthood on labor market outcomes also differ by field. We now study the labor market trajectories of all individuals with a college degree separately by their field of study.[43] As depicted in Figure 10, after childbirth earnings decrease for all high-educated women, while they persistently grow for male graduates. However, there is substantial heterogeneity by field.

Mothers who graduated in Medicine, Dentistry, Pharmacy or in Science and Mathematics face the lowest earnings loss and male graduates in Medicine, Dentistry, Pharmacy, Social Sciences and Services register the highest increase in earnings relative to just before the birth of their first child. The long-term child penalty is lowest for women in the male-dominated fields of Science and Mathematics (35.7%) and Informatics (40.1%), whereas it is highest for female graduates in Services (58.2%) and Health

[42] The pre-trend in terms of participation for noncollege-educated women is flatter and starts decreasing later when not imposing a minimum earnings threshold for the participation indicator.

[43] We omit General Programmes as this is a very small field among the college-educated.

(51.1%). Yet, overall there is no clear correlation between a field's gender ratio and its child penalty as e.g. also the field of Services is slightly male dominated. Furthermore, since individuals sort into fields of study based on unobservables such as ability, motivation and preferences, this pattern may be due to selection and not necessarily reflect causal effects of different fields. It is, however, conceivable that employers in male-dominated fields offer more family-friendly jobs without reducing pay as a compensating differential in order to attract qualified women. Rates of skill depreciation may also be higher in these fields so that women may avoid (lengthy) career interruptions to not lose out on promotion opportunities or fall (further) back behind their male peers. Long-term child penalties for all fields and outcomes are provided in Appendix table 23, but for reasons of brevity will not be discussed in detail.

We also find large differences by field regarding women's participation, working hours and wage rate trajectories. Participation rates and working hours again decrease least for female graduates in Medicine, Dentistry, Pharmacy, and Science and Mathematics, which may be because these fields tend to take longer to complete, increasing costs of career interruptions and working time reductions. Male college graduates hardly adjust their labor supply after they have their first child. Their wage rates steadily increase as they continue to climb the career ladder, though growth rates differ by field. In contrast, women of all fields see gradual declines in their wage rates, but these estimates are less precise and partly statistically insignificant. The relative importance of participation, working hours and wage rates differs by field, so that also the rankings in terms of long-term child penalties differ for these outcomes. The main driver of the earnings child penalty again seems to be women's reduction in working hours, but they also fall back compared to men because the latter continue to enjoy rising hourly wages.

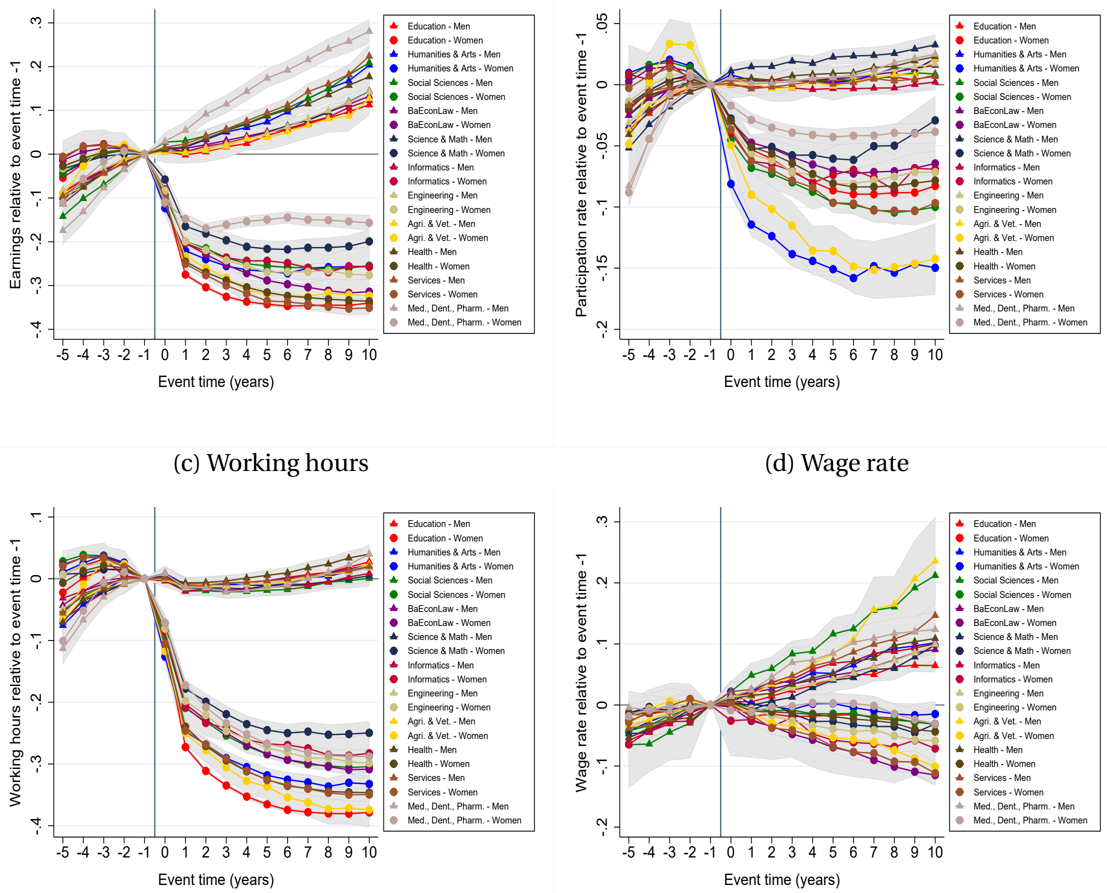
3.4.2 Labor market trajectories of couples by their relative earnings potential

To investigate the role of household specialization based on comparative advantages and bargaining power, we need a measure of individuals' earnings potential. As mentioned above, actual earnings before having the first child are typically measured at an age where earnings are unstable and are thus less suitable for our purposes. Instead,

Figure 10: Labor market trajectories by field of study

(a) Earnings (b) Participation

(c) Working hours (d) Wage rate



Note: The figures show the estimated coefficients (with confidence intervals) of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child separately for men and women, i.e. P_{τ}^{g} (as defined in 3.2).

we will use six proxies for earnings potential (three of these are discussed in Appendix 3.6.3).

It is not straightforward what the optimal measure of relative (lifetime) earnings potential would be. Both partners' pre-birth earnings potential plays an important role as it is predictive of future earnings. It is less clear how earnings potential before birth, but also for later years should be determined. Individuals' level and field of education, occupation and work experience are important components[44], but may be

[44] We do not observe individuals' occupation and work experience, but approximate the latter by age.

an insufficient measure of unobserved individual ability/productivity. Different types of education and occupations have differing earnings trajectories that may also vary by gender.[45] It also matters how many years individuals will remain active in the workforce and reap market returns. If couples have more children after the first one, mothers will incur further career interruptions for at least the length of maternity leave which may lead to (further) skill atrophy. These aspects of earnings capacity are to varying degrees captured by our proxies. Men and women may also derive differential utility from spending time with their children, such that a more traditional division of labor may be utility maximizing. Our measures of earnings potential are agnostic of such differences in preferences.

Combination of educational level

We divide our household sample by partners' combination of educational level into seven categories: 1) both have no college degree, 2) only the man has a college degree, 3) only the woman has a college degree, 4) both have bachelor's degrees, 5) the man has a master's degree, the woman has a bachelor's degree, 6) the man has a bachelor's degree, the woman has a master's degree, 7) both have master's degrees. The level of education is easily observable and clearly correlates with earnings (potential). Yet, it is only a crude measure of individual productivity and ignores that men and women tend to choose fields at the same educational level that lead to distinct earnings opportunities.[46]

The findings from our separate event-study regressions for the seven sub-samples are presented in figure 11. Earnings decrease by far the most after childbirth for women who do not have a college degree independent of whether their partner does. Women who have a master's degree and are in a partnership with another master's graduate experience the lowest drop in earnings followed by all women who have a higher education than their partner. Nonetheless, none of them converge back to their pre-birth earnings level. Earnings increase for all men, but most for master's graduates who form a household with another master's graduate and for men who surpass their partner in terms of education. The long-term child penalties are largest for couples

[45] As mentioned above, the gender wage gap literature finds that human capital variables like education contribute little to the gap in recent years, but that gender differences in occupation are still relevant.

[46] Similar to the other proxies that require information on individuals' education, we can only conduct this part of the analysis for couples where we know both partners' educational attainment (see table 21).

where the male partner has a higher education than the female and lowest in the reverse cases. Long-term child penalties for all three measures of relative earnings potential in this section are provided in table 24, but for reasons of brevity will not be discussed in detail.

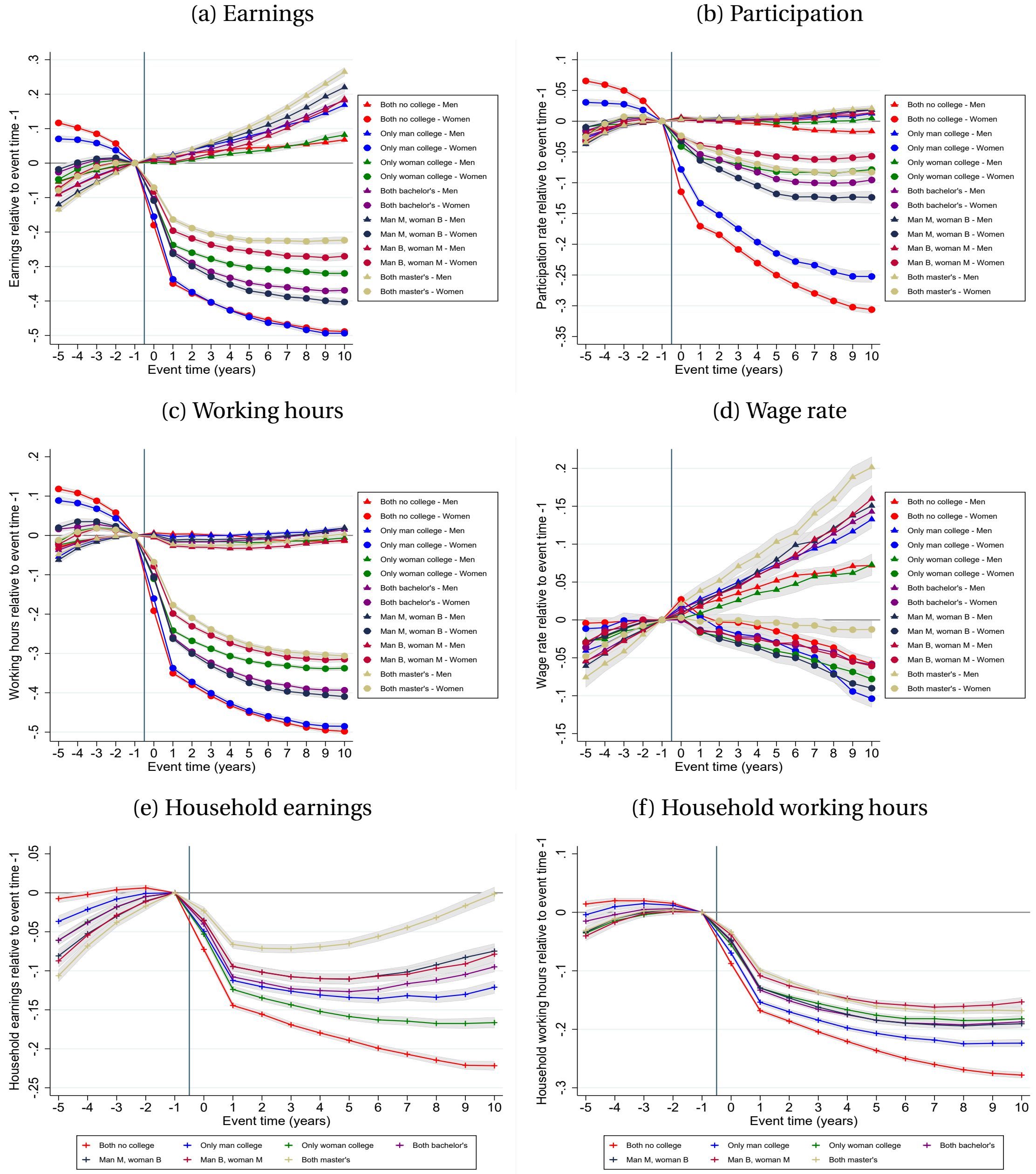
We find a similar picture for participation rates and working hours. Women who surpass their partner in terms of education reduce their labor supply less than women in partnerships with the reverse constellation. Men's participation rates and working hours hardly change after becoming a parent. The pattern for women's wage rate trajectories is less clear and the estimates come with larger confidence intervals. Wage rates decrease for all women, though the effects are initially insignificant for master's graduates who have an equally high-educated partner. These men by far reap the largest increase in wage rates leading to a long-term child penalty of 22% in this group. Again, the earnings' trajectories seem primarily shaped by adjustments in working hours.

We also investigate how partners' labor market adjustments after parenthood affect their total household earnings and working hours from employment, which are important determinants of household utility. Household earnings decrease for all couples after childbirth though they recover to varying degrees if at least the father has any type of college degree. Even for couples where both have a master's degree it takes ten years to return to their pre-birth earnings level. Driven by women, total household working hours drop considerably after childbirth with hardly any recovery. In sum, women seem to make career choices after childbirth based on their absolute and within-household earnings potential, while men do not adjust their labor supply irrespective of their relative or absolute earnings capacity. Given that their wage rates and hence earnings increase, we also find no evidence of men moving to potentially more family-friendly jobs that pay less as a compensating differential and/or offer fewer opportunities for career advancement.

Combination of field of study

Next, we use the earnings level of the fields of study of college-educated couples as proxy. We split the fields by the average earnings of our sample in the 5-year period before birth into high-, medium-, and low-earnings fields. High-earnings fields comprise Business, Economics, Law, Science, Mathematics, Informatics, Engineering, Manufacturing, Construction, Medicine, Dentistry and Pharmacy. Medium-earnings fields are

Figure 11: Labor market trajectories by combination of educational level



Notes: Figures (a)-(d) show the estimated coefficients (with confidence intervals) of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child separately for men and women, i.e. P_{τ}^{g} (defined in 3.2). Figures (e) and (f) show the estimated coefficients of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child for household earnings and working hours. Equation 3.1 is modified to include age dummies for both partners. The legend abbreviations B and M signify Bachelor's and Master's degree, respectively.

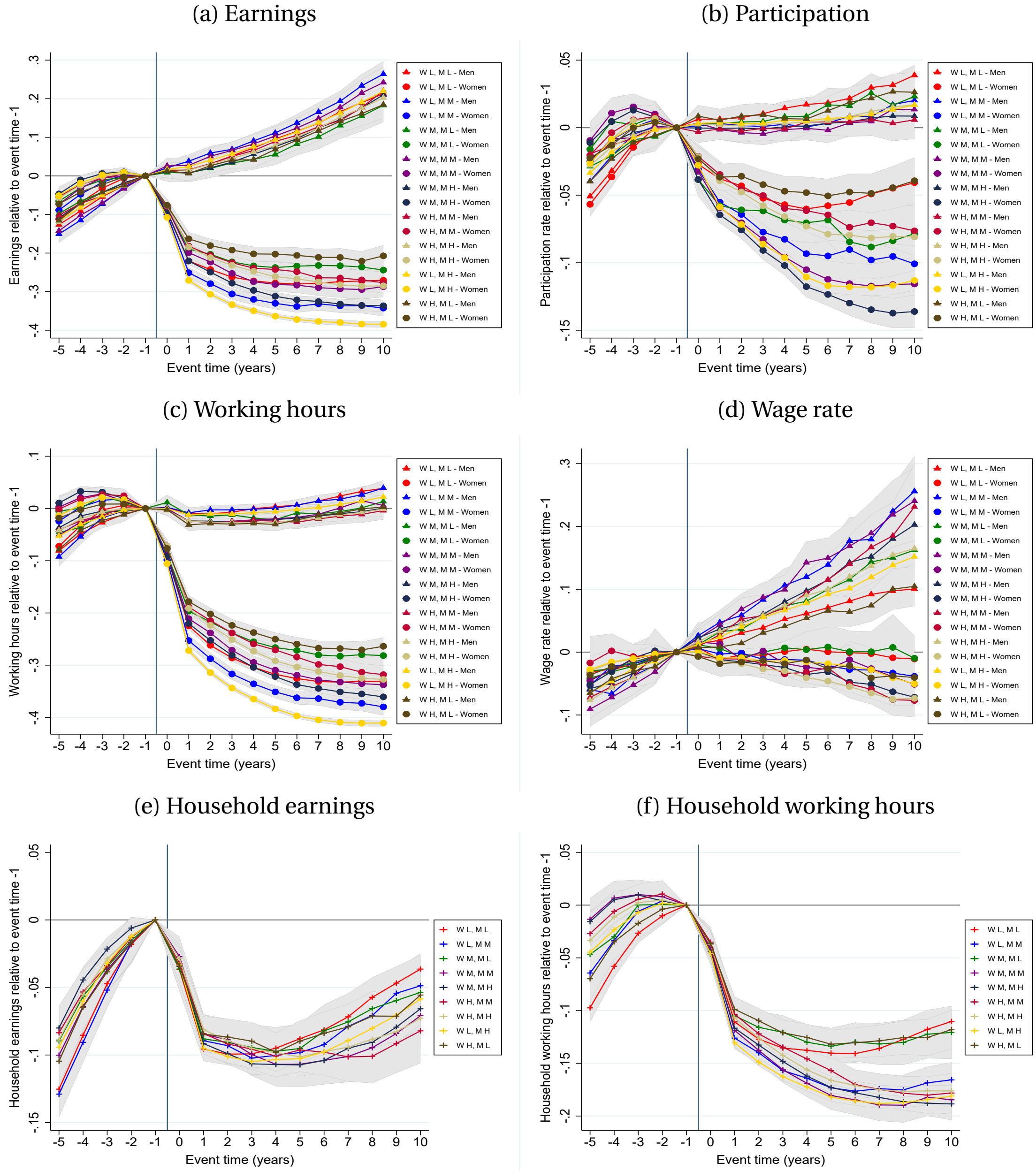
General Programmes, Social Sciences, Agriculture, Veterinary and Services, while we classify Education, Humanities, Arts and other Health programs as low-earnings fields. The combination of men's and women's fields of study yields nine groups of relative household earnings potential. The (dis-)advantages of this proxy are similar to using the combination of educational level. The field of study is only a coarse measure of individual productivity/ability and broad fields of study comprise programs that have varying earnings prospects and gender ratios.

Figure 12 presents the results. While before childbirth earnings increase for all graduates, women's earnings sharply drop after having a child without any meaningful recovery during our observation period. In contrast, men's earnings continue on their growth path with fairly small differences across household categories. Similar to our findings above, women that are in a higher-earnings field than their partner experience a comparatively smaller earnings loss. Consequently, long-term child penalties are lowest for women who are in a higher-earnings field than their partner.

A similar pattern holds for participation and working hours as women who are in higher-earnings fields than their partners tend to be less likely to leave the workforce and they reduce their hours less after having children. However, women in low-earnings fields with a partner from such a field are also less likely to withdraw from the labor market and their participation rate starts recovering six years after birth. It may be that these couples are financially more dependent on the woman's income. Men's labor supply seems hardly affected by parenthood independent of their relative earnings potential. The effects of having the first child on wage rates do not follow a clear pattern. Women in the highest-earnings fields experience the largest wage reduction after parenthood, which could suggest higher skill atrophy in these fields, while men's hourly wages rise markedly.

Total household earnings increase considerably in the pre-birth period, but subsequently drop for all households with varying degrees of recovery that are driven by men's earnings growth. The drop in total household working hours is persistent for most groups. Again, we find no indication of household specialization based on comparative advantage as men do not seem to adjust their labor supply and career choices after parenthood. Women remain more attached to the labor market if they have a degree that offers better earnings prospects, but this happens independent of their partner's

Figure 12: Labor market trajectories by combination of field of study



Notes: Figures (a)-(d) show the estimated coefficients (with confidence intervals) of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child separately for men and women, i.e. P^g_τ (defined in 3.2). Figures (e) and (f) show the estimated coefficients of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child for household earnings and working hours. Equation 3.1 is modified to include age dummies for both partners. The legend abbreviations W and M signify Women and Men, respectively, while L, M and H indicate low-, medium- and high-earnings fields, respectively.

earnings capacity. Yet, a less traditional division of labor could lead to higher household earnings for couples where the woman is in a high-earnings field.

Predicted life-cycle earnings

We construct a population sample that comprises all childless men and fathers in the period before their first child and use it to predict individuals' lifetime earnings potential in the absence of children from the year before first birth until the year they turn 60. To that end, we run a regression of earnings on fully interacted dummy variables for age, field (12) and level (9) of education. We discount predicted annual earnings by 3% and sum them up to obtain predicted lifetime earnings. Subsequently, we divide couples into four categories: 1) woman is predicted to earn more than 50,000 euros more than her partner, 2) woman is predicted to earn ± 50,000 euros of her partner's lifetime earnings, 3) woman is predicted to earn between 50,000 to 200,000 euros less than her partner, 4) woman is predicted to earn more than 200,000 euros less than her partner.

This proxy accounts better for gender differences in educational choices than the broad field or level of education. Interacting age with education also incorporates differential experience profiles for different types of education. The proxy represents a long-term planning horizon as it comprises both predicted current and future earnings. It also takes into account within-couple age differences, such that e.g. the younger spouse may reap higher lifetime earnings even if her/his annual earnings are lower as she/he will be active on the labor market for a longer period. However, the earnings returns at higher ages are based on an increasingly selective and small sample, i.e. men who had their first child quite late or never had children. Women may also reap differential returns to education and experience compared to men, so that these earnings predictions may give a less accurate estimate of women's earnings capacity.[47] The returns to (types of) education may also change over time, but since such changes

[47] A similar sample of women in the Dutch population would be even more selective for several reasons: 1) the number of women who remain childless is relatively low, 2) women who have children on average do so earlier than men, leading to a shorter pre-birth observation period, 3) working reduced hours is common especially among older generations so that we would estimate the returns to part-time work, and 4) non-participation rates are also higher among older generations than among the women giving birth during our observation period.

are hard to predict for most people, they would likely still draw on current returns when making decisions on the division of labor.

The findings are presented in figure 13. Women's earnings losses are fairly similar across groups in the year of birth as they are subject to the same maternity leave regulations, but start diverging after that. Women who are predicted to out-earn their partner or to earn roughly the same over the remainder of their working life face smaller earnings losses than women who are predicted to earn less than their partner, though the differences are small. Men's earnings are either unaffected by childbirth or gradually decrease somewhat thereafter, though there is no clear pattern discernible.

Looking at the individual components of earnings, we see that women's labor supply trajectories mirror their earnings paths. Men's participation rates and working hours decrease somewhat after birth, but this decline occurs gradually and is quite similar across categories of relative household earnings potential. Mothers' wage rates consistently decrease after birth with the decline again being larger for relatively high-earning women. Men either register no change in their wage rates or a minor decline that does not come close to women's reduction in wages. For all four outcomes, long-term child penalties are of reasonably similar magnitude across groups. The largest loss in total household earnings after childbirth is registered by couples where the woman is predicted to out-earn her partner. It seems that these households do not optimally use women's capacity on the labor market to realize higher household income. However, differences across types of households are relatively small again, especially with regards to household working hours. Overall, households do not appear to put much weight on expected future earnings as we detect fairly small differences across groups even though their relative earnings potentials vary substantially.

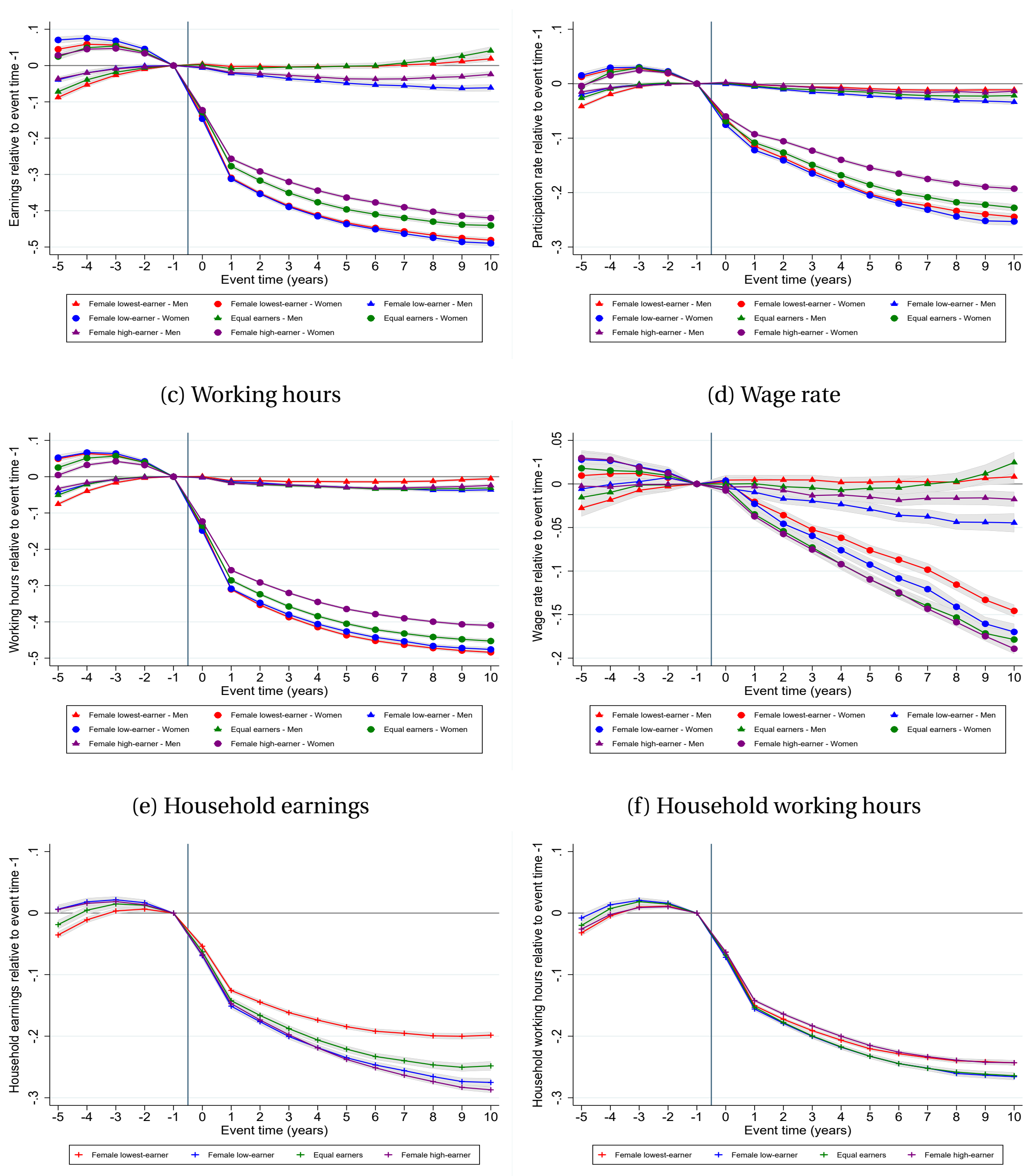
In Appendix 3.6.3, we discuss three other measures of relative earnings potential, namely the within-couple age difference, partners' relative pre-birth wage rate and women's share in the predicted total household earnings in the year before birth. The results again show little indication of household specialization based on comparative advantages.

Figure 13: Labor market trajectories by predicted life-cycle earnings

(a) Earnings (b) Participation

(c) Working hours (d) Wage rate

(e) Household earnings (f) Household working hours



Notes: Figures (a)-(d) show the estimated coefficients (with confidence intervals) of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child separately for men and women, i.e. P_τ^g (defined in 3.2). Figures (e) and (f) show the estimated coefficients of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child for household earnings and working hours. Equation 3.1 is modified to include age dummies for both partners.

3.4.3 Use of formal child care

Women with higher earnings potential reduce their working hours less after the birth of their first child and their partners do not compensate by reducing their working hours. To shed more light on how these households cope with combining market work and family duties, we consider the use of formal child care. Use of child care is measured as a household's total annual costs spent on formal child care that is eligible for government subsidies and as total hours that a household's children spend in formal child care in a year.[48] To that end, we run panel random effects regressions of these child care use indicators on our proxies for men's and women's earnings capacity, year fixed effects and event-time fixed effects covering the event time period 0 to 10. Our earlier results indicate that when deciding about labor supply, individuals do not take their relative earnings potential in the household into account. Therefore, we associate the use of formal child care to the absolute earnings potential of both partners in the household.

The findings in table 22 indicate that the use of formal child care both in terms of total annual costs and hours of care is more responsive to an increase in women's earnings potential. For women, having a master's degree compared to no college education is associated with additional child care spending of 3285 euros per year, while a similar increase in the male partner's education is associated with less than half the increase in spending. As shown in panel II, if the male partner is in a high-earnings instead of a low-earnings field of study, the household spends on average about 838 euros more on child care, while use of formal care correlates with an almost threefold higher increase if the female partner would make such a move. Lastly, an increase in women's predicted life-cycle earnings is also associated with a larger increase in use of formal child care than a rise in men's predicted life-cycle earnings. Overall, this correlational analysis suggests that in order to combine work and home production, mothers with higher earnings capacity and stronger attachment to the labor market buy more formal child care. Appendix table 3.6.4 shows results for the three measures of earnings potential discussed in appendix section 3.6.3. It confirms the pattern found here that use of formal child care is more sensitive to women's earnings potential than to men's.

[48] We do not restrict use to hours of care for the first child as our event-study estimates also include the effect of children born after the first one.

Table 22: Use of formal child care by measure of earnings potential

	Costs for care		Hours of care	
	$\hat{\beta}$	s.e.	$\hat{\beta}$	s.e.
I. Level of education				
Man bachelor's degree	872.56	(14.65)	134.87	(2.34)
Man master's degree	1850.64	(18.79)	285.48	(2.98)
Woman bachelor's degree	1677.78	(14.28)	266.75	(2.29)
Woman master's degree	3285.36	(18.67)	516.46	(2.97)
II. Field of study				
Man medium-earnings field	616.42	(38.00)	98.46	(5.99)
Man high-earnings field	837.93	(26.95)	132.82	(4.25)
Woman medium-earnings field	1588.46	(29.56)	245.57	(4.64)
Woman high-earnings field	2228.90	(24.45)	349.32	(3.87)
III. Predicted life-cycle earnings				
Man's predicted lifetime earnings	0.002595	(0.000026)	0.000404	(0.000004)
Woman's predicted lifetime earnings	0.004740	(0.000027)	0.000748	(0.000004)

3.5 Conclusion

A number of recent studies has shown that parenthood comes with large earnings penalties on women, while men are barely affected by having children. We confirm this result for the Netherlands and document a large and persistent earnings child penalty that is primarily driven by women's marked reduction in working hours and to a lesser extent by lower participation and a gradual decline in wage rates. Child penalties differ by individuals' level of education and their field of study at college. Women who graduated in the male-dominated fields of Science and Mathematics, and Informatics face the lowest earnings penalty, but this may be due to self-selection into fields and not necessarily reflect an effect of the field itself. Yet, it is possible that employers in these fields offer more family-friendly jobs without reducing pay as a compensating differential in order to attract qualified women. It could also be that rates of skill depreciation are higher in these fields so that women avoid (lengthy) career interruptions to not fall back behind their male peers.

One of the potential causes of the child penalty discussed in the literature is household specialization based on comparative advantages in labor market work and child care. Prior research concludes that biological factors can only explain part of short-run child penalties, but not (the persistence of) long-run penalties so that women do not seem to have a comparative advantage in child care (Andresen and Nix, 2019; Kleven et al., forthcoming). This leaves room for household specialization based on partners' relative earnings potential within the household. Women who have a higher earnings capacity than their partner might remain more attached to the labor market, while their partners take over more child care duties compared to women with a low within-household earnings potential. To test this hypothesis, we use various measures of relative earnings potential. All of these have advantages, but also limitations that we discuss in sections 3.4.2 and 3.6.3.

Nonetheless, our findings across these proxies consistently show little evidence for household specialization based on comparative advantages and/or bargaining power. Men's labor supply on both the extensive and intensive margin is barely affected by fatherhood irrespective of their relative earnings potential. We partly find some small decreases in men's wage rates and total earnings for some types of households, which could suggest moves to more family-friendly jobs. These findings are not robust across our proxies for earnings potential and do not show a clear pattern. Men's gradual declines in wage rates and earnings are also considerably smaller than the decreases in wages and earnings that women typically experience.

Women's earnings losses are smaller if they have a higher relative earnings capacity and they reduce their labor supply less than women with low relative earnings capacity. Given the absence of effects on men, this pattern does not seem to be a result of within-household negotiations about the division of market and household work, even when this could lead to gains in household earnings. It could instead be driven by differences in absolute earnings potential among women, such that higher-educated/higher-earning women remain more attached to the workforce after having children. Descriptive evidence suggests that households where women have a high earnings capacity make more use of formal child care to enable mothers to combine work and family. Our results also reject the unitary household model which does not allow for distinct preferences of men and women in a household and requires, among others, that marginal compensated wage changes of two individuals in a household have the same effect on each other's labor supply.

We find little evidence for household specialization even though there are hardly any institutional hurdles to divide household and labor market in a gender-neutral way in the Netherlands. Based on our results we cannot draw any conclusions about whether the labor market trajectories we find are instead shaped by preferences or by gender norms. Part-time work, especially among women, has a long tradition in the Netherlands and an entitlement to working reduced hours was also entered into law in 2000.

3.6 Appendix

3.6.1 Long-term child penalties - sample of individuals

Table 23: Long-term child penalties - sample of individuals

	Earnings	Participation	Working hours	Wage rate
I. Full sample				
	46.8%	17.7%	43.4%	16.7%
II. Level of education				
College	50.0%	9.2%	36.7%	20.9%
No college	48.5%	24.3%	43.8%	11.0%
III. Field of study				
Education	45.8%	9.0%	40.4%	9.9%
Humanities & Arts	46.4%	17.1%	35.1%	12.0%
Social Sciences	46.7%	10.8%	30.5%	24.9%
Business, Economics & Law	45.6%	8.0%	33.0%	21.2%
Science & Mathematics	35.7%	6.3%	25.4%	13.3%
Informatics	40.1%	7.1%	29.2%	17.7%
Engineering	43.1%	8.9%	31.6%	15.8%
Agriculture & Veterinary	45.5%	16.3%	39.6%	31.7%
Health	51.1%	10.1%	38.3%	15.3%
Services	58.2%	10.3%	36.8%	26.4%
Medicine, Dentistry & Pharmacy	45.3%	6.3%	32.4%	16.2%

3.6.2 Long-term child penalties by relative earnings potential

Table 24: Long-term child penalties by relative earnings potential

	Earnings	Participation	Working hours	Wage rate
I. Combination of level of education				
Both no college	56.7%	29.1%	48.4%	13.5%
Only man college	76.8%	26.5%	50.6%	29.4%
Only woman college	38.4%	8.3%	33.2%	13.8%
Both bachelor’s degrees	57.1%	11.4%	40.8%	21.7%
Man master’s, woman bachelor’s	69.7%	14.3%	42.9%	28.4%
Man bachelor’s, woman master’s	42.9%	7.1%	30.4%	20.3%
Both master’s degrees	49.4%	10.3%	31.0%	22.2%
II. Study field combination				
Both low-earnings field	48.3%	7.9%	36.7%	11.5%
Woman low-, man medium-earnings field	63.5%	12.1%	41.8%	30.4%
Woman medium-, man low-earnings field	40.2%	10.0%	29.4%	15.9%
Both medium-earnings field	52.3%	12.9%	34.3%	29.2%
Woman medium-, man high-earnings field	58.9%	14.5%	36.1%	30.4%
Woman high-, man medium-earnings field	46.0%	8.2%	31.5%	27.8%
Both high-earnings field	48.2%	9.8%	32.6%	23.8%
Woman low-, man high-earnings field	68.4%	13.0%	43.3%	24.2%
Woman high-, man low-earnings field	33.6%	6.5%	26.6%	12.7%
III. Woman’s predicted relative life-cycle earnings				
> 50,000 euros more than partner	40.0%	18.1%	38.9%	17.4%
± 50,000 euros of partner’s earnings	48.1%	20.8%	42.4%	20.3%
50,000-200,000 euros less than partner	41.2%	22.1%	44.0%	11.8%
> 200,000 euros less than partner	51.0%	23.3%	47.8%	15.7%

3.6.3 Event-study analysis for further measures of relative earnings potential

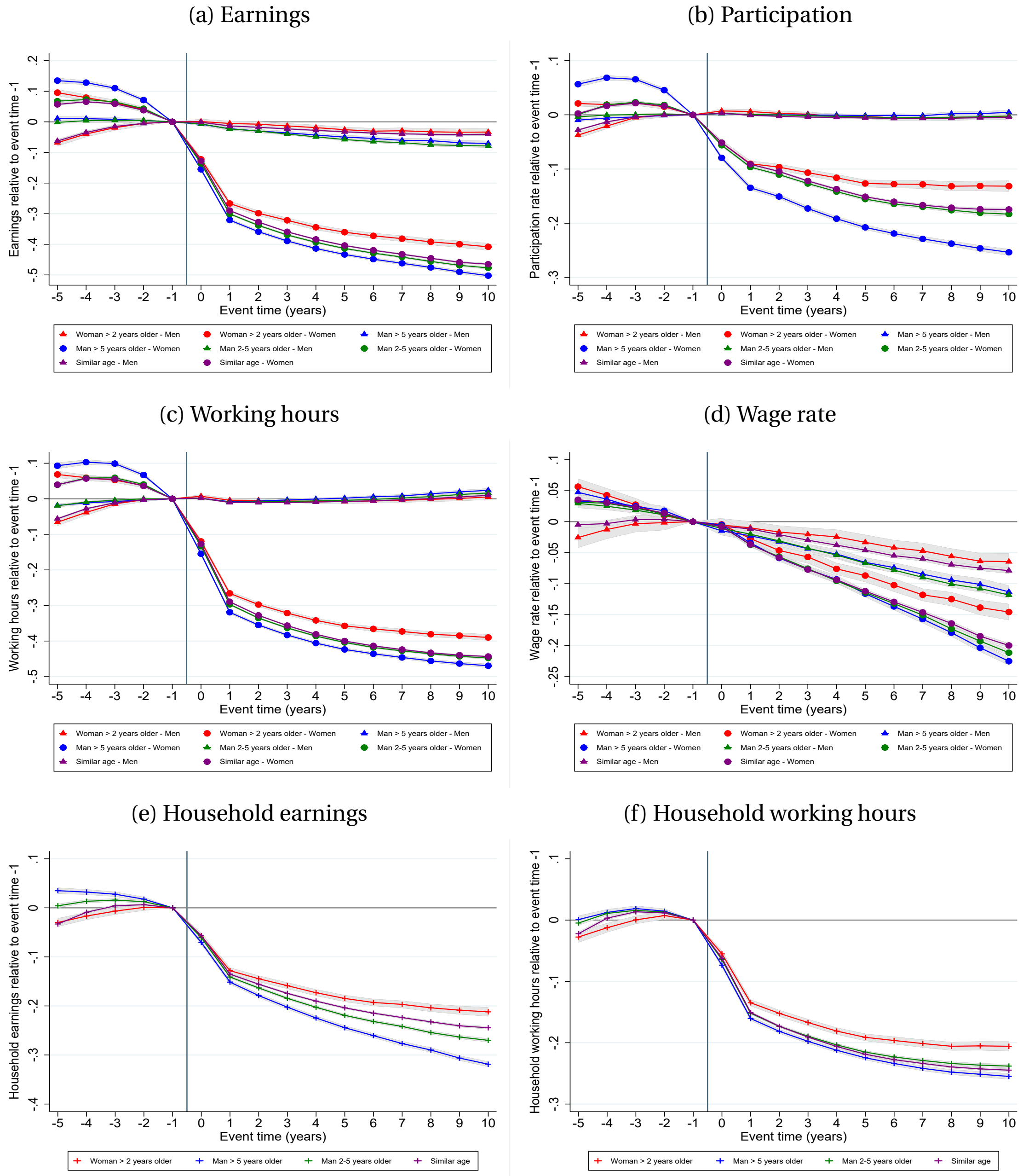
As robustness checks, we discuss three other measures of relative earnings potential, namely the within-couple age difference, partners' relative pre-birth wage rate and women's share in the predicted total household earnings in the year before birth. Long-term child penalties for all three measures are shown in table 25, but for reasons of brevity will not be discussed in detail.

Within-couple age difference

We split households by their within-couple age difference into four categories: 1) woman is more than 2 years older than the man, 2) age difference within ± 2 years, 3) man is 3 to 5 years older than the woman, 4) man is more than 5 years older than the woman. The older partner in a relationship may have higher (life-cycle) earnings and more bargaining power in the negotiations about the division of care and market work.

As shown in figure 14, earnings, participation rates and working hours decrease markedly for women in all sub-samples after having children and this downward trend continues until the end of our observation period. The drop is smallest for women who are more than two years older than their partner and highest for women whose partner is more than five years older than they are, suggesting differences in bargaining power. Yet, men's earnings decline only slightly and their labor supply remains unchanged irrespective of their relative age. Long-term penalties are highest for women with a considerably older partner, but the differences across the four categories are relatively small. Wage rates gradually decrease for all men and women, but women who are more than two years older than their partner again experience the smallest decline and the lowest long-term child penalty. Overall, labor market trajectories tend to differ little by relative-age group, which suggests that this is not an important factor that couples take into account in their division of labor. Nonetheless, total household earnings and working hours decrease less for households where women remain more attached to the labor market.

Figure 14: Labor market trajectories by within-couple age difference



Notes: Figures (a)-(d) show the estimated coefficients (with confidence intervals) of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child separately for men and women, i.e. P_τ^g (defined in 3.2). Figures (e) and (f) show the estimated coefficients of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child for household earnings and working hours. Equation 3.1 is modified to include age dummies for both partners.

Relative pre-birth wage rate

Next, we classify our household sample by their relative wage rate in the year before childbirth into three categories: 1) woman earns more than 3 euros more per hour than her partner, 2) woman earns ± 3 euros of her partner's hourly wage, 3) woman earns more than 3 euros less per hour than her partner. Hourly wages are a direct measure of individual productivity prior to having a child. Women with higher (relative) wage rates face higher costs of career interruptions and may remain more attached to the labor market. Like observed total earnings, this proxy may be subject to reversion to the mean. Individuals with very high (low) pre-birth wage rates may experience future decreases (increases) in their wage rate if their current wage has a large transitory (shock) component.[49]

The pattern we find in figure 15 conforms with expectations that women with a higher pre-birth wage rate than their partner experience a smaller earnings decline, are less likely to leave the workforce or reduce their working hours less than women with a lower relative wage. However, for each of these outcomes the differences across the three groups only amount to about 10 percentage points. Men who have partners that earn about the same wage or markedly more as they do before birth see large increases in earnings after birth, while only slightly reducing their labor supply. This drives up long-term earnings child penalties which are highest for mothers in these two household categories. Hourly wages of women with relatively high pre-birth wages decline most among all three groups of women, whereas their partners' wage rates increase considerably in the post-birth period. This suggests that reversion to the mean is a concern with this proxy for earnings capacity.

Given the mostly small differences among women and increasing wage rates for men with relatively low pre-birth wage rates, differences in household earnings and working hours are small. The results overall suggest that households hardly use relative pre-birth wages as a decision criterion in their negotiations over the distribution of market and household work, even though there may be scope to increase household earnings.

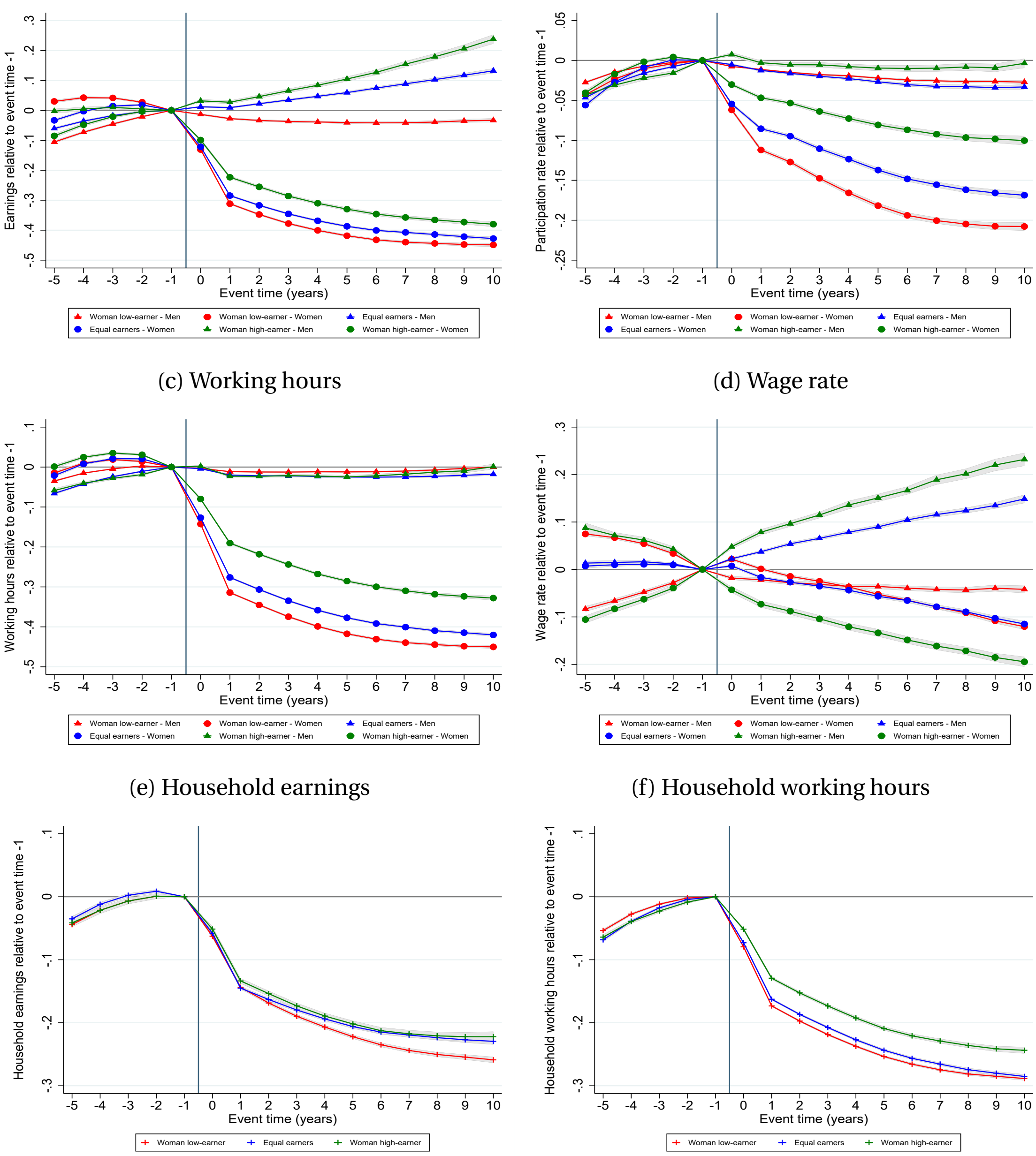
[49] Due to data availability, we can only calculate wage rates from 2006 onward and for employees, so that the sample reduces to births between 2007 and 2013 among couples where both were employed in the year prior to birth.

Figure 15: Labor market trajectories by relative pre-birth wage rate

(a) Earnings (b) Participation

(c) Working hours (d) Wage rate

(e) Household earnings (f) Household working hours



Notes: Figures (a)-(d) show the estimated coefficients (with confidence intervals) of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child separately for men and women, i.e. P_{τ}^{g} (defined in 3.2). Figures (e) and (f) show the estimated coefficients of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child for household earnings and working hours. Equation 3.1 is modified to include age dummies for both partners.

Predicted relative pre-birth earnings potential

Lastly, we use the population sample comprising all childless men and fathers in the period prior to their first child constructed in section 3.4.2 to predict pre-birth earnings potential. To that end, we run a regression of earnings on year fixed effects and on fully interacted dummies for age, field and level of education.[50] With the coefficients from this regression we predict earnings in the year before birth for both men and women. Predicted household earnings are then calculated as the sum of both partners' predicted earnings. Subsequently, we divide households by their relative pre-birth earnings potential into four categories: 1) woman's share in predicted household earnings ≥ 0.53; 2) 0.47 ≤ woman's share < 0.53; 3) 0.40 ≤ woman's share < 0.47; 4) woman's share < 0.40. This proxy offers similar advantages and disadvantages than using predicted life-cycle earnings, though it does not take a forward-looking perspective. It is also based on a selective sample as pre-birth earnings for men are mostly included for ages where the correlation between current earnings and lifetime earnings is low.

The results from our event-study analyses are documented in figure 16. For mothers, the picture is similar to using predicted life-cycle earnings as proxy for earnings potential. Differences in earnings losses start appearing one year after birth, but remain small. Women with the highest predicted share in total household earnings experience smaller earnings reductions than other women. Men that are predicted to contribute less or a similar amount to household earnings than their partner, realize large increases in earnings that continue throughout the 10-year post-birth horizon. Consequently, long-term earnings child penalties are largest for women in these two categories.

Women with a higher predicted contribution to household earnings reduce their labor supply less, both on the extensive and the intensive margin. Men barely adjust their working hours and rarely leave the labor force after having children. The small differences in long-term child penalties across groups therefore arise from women's differential adjustment to parenthood. Wage rates decrease for all women, though the decline is smallest for women who are predicted to contribute less than 40% to household earnings. There may be less scope for decreases in wage rates for lower-earning individuals (e.g. due to minimum wage laws). The earnings growth for men who are predicted to earn less or about the same as their partner is driven by continual

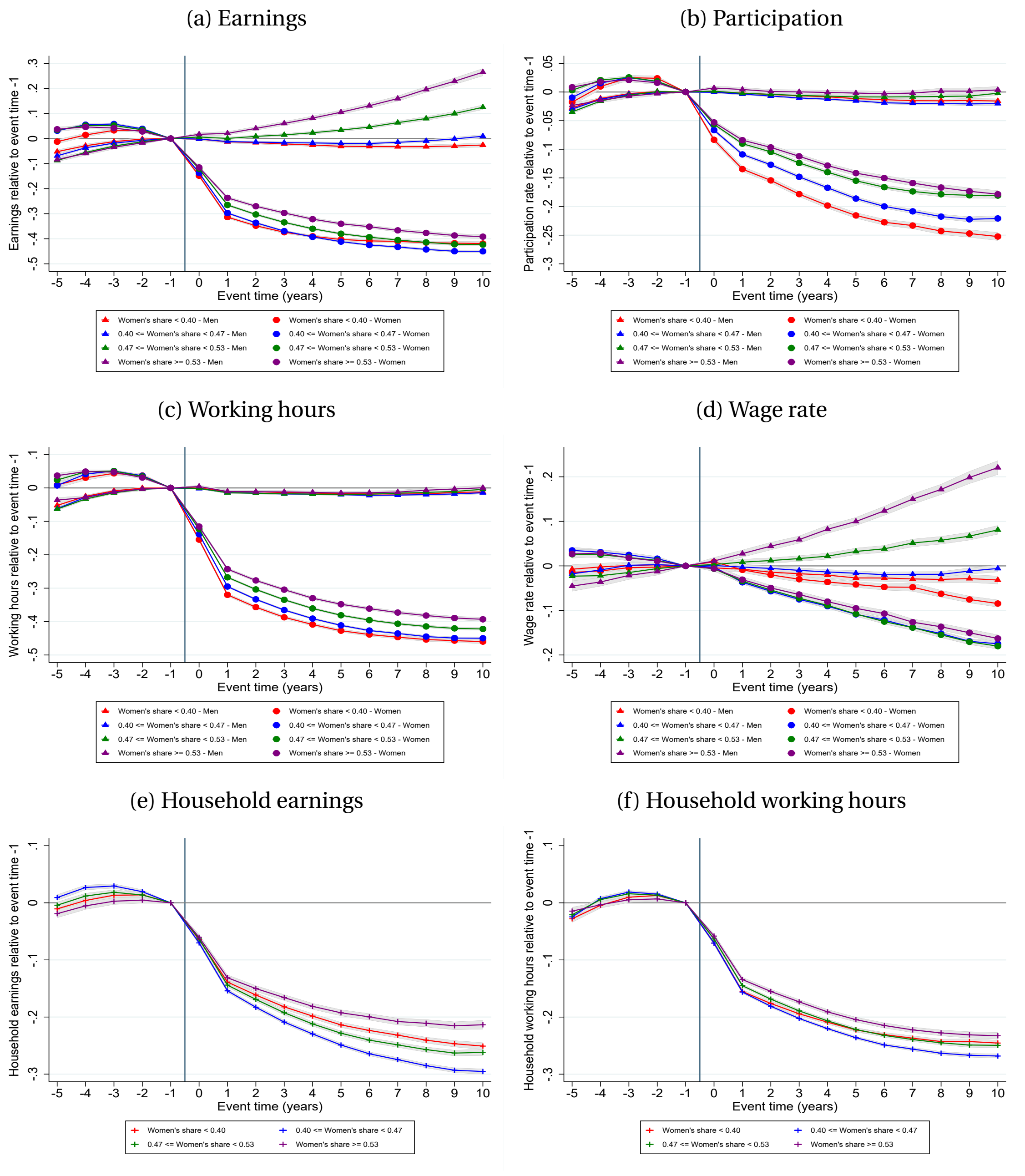
[50] We now distinguish between 111 fields of education and twelve levels of education.

increases in their hourly wages. Given the strong increase in earnings of relatively low-earning men, household earnings drop least after childbirth for this group compared to the other three types of households. The differences across groups are initially similar and start diverging in the year after birth, but remain relatively small during our observation period. A similar pattern can be found for household working hours. Again, we find little evidence of household specialization based on comparative advantages in market work as men's career paths seem independent of parenthood, while women's trajectories differ only moderately by their predicted pre-birth earnings potential.

Table 25: Long-term child penalties by relative earnings potential - robustness checks

	Earnings	Participation	Working hours	Wage rate
I. Within-couple age difference				
Woman > 2 years older	36.6%	12.9%	39.6%	7.2%
Similar age (± 2 years)	41.7%	17.0%	45.3%	11.0%
Man 3-5 years older	38.4%	18.1%	46.3%	7.5%
Man > 5 years older	42.4%	25.8%	49.1%	9.9%
II. Relative pre-birth wage rate of women				
> 3 euros more than partner	50.7%	9.7%	32.9%	32.2%
± 3 euros of partner's wage	54.5%	13.7%	40.3%	24.3%
> 3 euros less than partner	39.7%	18.1%	45.0%	5.8%
III. Woman's share in predicted pre-birth household earnings				
Woman's share ≥ 0.53	55.5%	18.2%	39.4%	31.6%
0.47 ≤ woman's share < 0.53	53.3%	17.9%	41.8%	25.3%
0.40 ≤ woman's share < 0.47	46.1%	20.2%	43.6%	16.8%
Woman's share < 0.40	37.4%	23.7%	44.7%	3.7%

Figure 16: Labor market trajectories by predicted relative pre-birth earnings potential



Notes: Figures (a)-(d) show the estimated coefficients (with confidence intervals) of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child separately for men and women, i.e. P_{τ}^{g} (defined in 3.2). Figures (e) and (f) show the estimated coefficients of the event-time dummies as a fraction of the predicted counterfactual outcome of no children in each year relative to the birth of the first child for household earnings and working hours. Equation 3.1 is modified to include age dummies for both partners.

3.6.4 Use of formal child care for further measures of earnings potential

Table 26 shows the results from our random effects regressions for the three measures of earnings potential discussed in the previous section. We again find that a household's use of formal child care correlates more strongly with an increase in women's earnings potential - as measured by their pre-birth wage rate and their predicted pre-birth earnings - than with an increase in men's. Households where women are older when having their first child also make considerably more use of child care, while no such association can be found for men.

Table 26: Use of formal child care by measure of earnings potential - robustness checks

	Costs for care		Hours of care	
	$\hat{\beta}$	s.e.	$\hat{\beta}$	s.e.
I. Age				
Man's age	1.84	(1.46)	0.12	(0.23)
Woman's age	159.16	(1.64)	24.92	(0.26)
II. Pre-birth wage rate of women				
Man's wage rate	34.33	(2.69)	5.15	(0.41)
Woman's wage rate	94.90	(8.82)	14.58	(1.35)
III. Predicted pre-birth household earnings				
Man's predicted pre-birth earnings	0.0534	(0.0006)	0.0083	(0.0001)
Woman's predicted pre-birth earnings	0.0987	(0.0007)	0.0155	(0.0001)

CHAPTER 4

Do doctors improve the health care of their parents? Evidence from admission lotteries[51]

4.1 Introduction

Many policy makers aim at equal access to health care for all. Even in countries with universal health insurance coverage and almost free health care, health care use may, however, differ between people for reasons unrelated to their health. These reasons include: i) information limitations about health risks, adequate preventive behavior or treatment options, ii) patients' inability to communicate with their health care providers, and iii) providers treating patients of different backgrounds differently. A recent literature examines the combined effect of these reasons by comparing outcomes of doctors and their relatives to those of a control group (Chen et al., 2019; Chou et al., 2006; Frakes et al., 2019; Grytten et al., 2011; Johnson and Rehavi, 2016; Leuven et al., 2013). The idea in these studies is that doctors and their relatives have full access to medical expertise and services so that their health care use and outcomes are not affected by any of these reasons.

[51] This chapter is based on Artmann et al. (forthcoming).

The main challenge in this literature is to isolate the effects of doctors' expertise and access to services from other factors that cause outcomes of doctors and their relatives to differ from those of other people. Doctors have a profession that comes with irregular working hours and is physically more demanding and more stressful than most other professions. Moreover, doctors select themselves into their profession which may be related to their initial health condition or their attitudes towards health. Similar concerns pertain to the relatives of doctors. Doctors typically come from more educated families, and doctors choose different partners and have different fertility patterns than non-doctors (e.g. Artmann et al., 2018). To deal with these issues, most existing studies use an extensive set of control variables, including risk factors and baseline health, and focus on specific health conditions.[52]

We contribute to this literature by using admission lotteries to medical school in the Netherlands to study how health outcomes of parents are affected by having a child who is a doctor. We compare outcomes of the parents whose child won the admission lottery to medical school and became a doctor to the outcomes of parents whose child lost this lottery and did not become a doctor. By looking at parents of doctors instead of doctors themselves, our results are not contaminated by the impact that working conditions may have on doctors' own health. At the moment the child applies to medical school, parents have long completed their education and made their occupation choice and other major labor market decisions. Therefore, parents of students who were admitted to medical school on the basis of lotteries are on average similar to the parents of applicants who lost the admission lottery, which eliminates selection bias. Furthermore, by looking at parents instead of other relatives, our results are not contaminated by doctors' partner choices and fertility decisions, or by endogenous study choices of siblings. Because children are more likely to care for aging parents than for aging uncles and aunts, parents are the relatives for whom it is most likely to find a treatment effect.

It is a priori not clear how parents' health care use and outcomes are affected by having a child who is a doctor. Various forces are at work. Doctors may provide in-

[52] Chou et al. (2006) and Johnson and Rehavi (2016) find a lower incidence of C-sections among doctors and their relatives than among other women in Taiwan and the US. Grytten et al. (2011) find that doctors and their relatives are more likely to have a C-section than other women in Norway. These different results can in part be explained by the different financial incentives in hospitals between the countries. Frakes et al. (2019) find that military doctors in the US do only slightly better than other military officers. Using Swedish admission lotteries to medical school and an event study comparing doctors to lawyers, Chen et al. (2019) find that relatives of doctors have more favorable health outcomes.

formation about preventive behavior. This reduces parents' demand for care if they behave more healthy, but may also increase demand for care through, for example, regular screenings and flu shots. Doctors may also convince parents to take prescribed medication and to complete treatments. This does not need to change the amount of formal care, but would increase the quality of care and thus improve parents' health outcomes. Furthermore, doctors may be better in recognizing symptoms in an early stage. This may lead to earlier diagnosis, which increases health care use in the short run, but may reduce it in the longer run. Finally, doctors may use their knowledge and network to obtain treatment for their parents. They could try to direct them immediately to a specialist rather than first going to a GP. Or they may provide additional information to the GP or specialist to help them make a better diagnosis and decision about providing subsequent treatments. This changes the type of health care and may also affect the costs of health care.[53] All forces operate in the direction of lowering the mortality of doctors' parents, which is our key outcome variable. It is an empirical question whether the combined effect of these forces increases or decreases health care use of doctors' parents. In our analysis we consider total health care costs, different types of health care use and various hospital diagnoses and medication use. This provides a detailed picture of how doctors affect the health care of their parents.

We use data from different registers that are available at Statistics Netherlands and that can be linked at the individual level and at the parent-child level. We combine the registers on admission lotteries for medical school, on educational attainment, on health care professionals, on mortality, and on health care use and costs, covering the full population.

When we consider the full population independent of children's level of education, we find strong associations between children having a medical degree and parents' mortality and health care use. Fathers and mothers of doctors live longer, have lower health care costs and are less likely to visit a GP, to be hospitalized or to take any prescription medication. They are, however, slightly more likely to be treated by a specialist. These associations are weaker, but still hold when we restrict the sample to parents of children with a college degree.

[53] We ignore that becoming a doctor has substantial earnings returns (Ketel et al., 2016), which could increase health investments for parents. Furthermore, being a doctor may change labor supply and the amount of leisure available to meet parents. Both channels are probably of second order importance in a small country like the Netherlands with extensive universal health insurance.

Next, we exploit the randomization of the admission lotteries to medical school to control for selection into the medical profession. We use the result of the first admission lottery as instrumental variable for practicing as a doctor. The estimation results show causal effects on mortality which are close to zero and not significantly different from zero. For health care use and costs most estimates are not significantly different from zero, although for some outcome variables estimates are too imprecise to rule out substantial effects. Taken together, the results indicate that having access to medical expertise and services through a child who is a doctor is not an important cause of differences in parents' health care use and mortality.

Our paper is related to three other literatures. First, to the literature on inequity in access to health care, which tends to conclude that access is biased towards high SES groups.[54] Second, to the literature on the effect of education on health outcomes, which shows mixed findings about the causal impact of education on health.[55] And third, to the recent literature on the relationship between adult children's education and parents' longevity, where studies find a positive association and sometimes a positive causal impact.[56] Our paper is most closely related to Chen et al. (2019), who study the same research question using admission lotteries to medical school in Sweden and an event study comparing health outcomes of relatives of doctors and lawyers.[57] Their results differ from ours. After the presentation of our findings, we discuss possible reasons for these differences.

[54] See Van Doorslaer et al. (2006) and Van Doorslaer et al. (2004). Individuals with higher education and/or income have better access to primary care (Angerer et al., 2019; Olah et al., 2013), to certain health services after a stroke (Kapral et al., 2002) or to specialized cardiac services (Alter et al., 1999) and have shorter waiting times for non-emergency hospital treatment (Monstad et al., 2014; Moscelli et al., 2018; Siciliani and Verzulli, 2009).

[55] Higher educated individuals live longer and are in better health throughout the lifespan. The evidence on a causal link is, however, mixed. Lleras-Muney (2005), Oreopoulos (2006) and Van Kippersluis et al. (2011) find that more education improves health outcomes, but Clark and Royer (2013), Meghir et al. (2018) and Malamud et al. (2018) find no support for this. See Galama et al. (2018) and Eide and Showalter (2011) for reviews.

[56] See Friedman and Mare (2014), Torssander (2013, 2014) and Zimmer et al. (2007) for correlational studies. Lundborg and Majlesi (2018) and De Neve and Fink (2018) apply instrumental variable approaches to estimate causal impacts. Fadlon and Nielsen (2019) analyze how health behaviors and investments are shaped through intra- and intergenerational family spillovers. They find that spouses and adult children immediately increase their health investments and improve their health behaviors in response to family health shocks.

[57] We wish to point out that our paper is not written to replicate Chen et al. (2019). We requested the data for this project from Statistics Netherlands in September 2017, long before we saw a first draft of the Chen et al paper in January 2019.

This paper proceeds as follows. Section 4.2 provides details on the health care system in the Netherlands and the admission lotteries. Section 4.3 describes the data. Section 4.4 first discusses the associations between having a child who is a doctor and parents' mortality and health care use, then it introduces the empirical approach and presents instrumental variables estimates of the causal effects. Section 4.5 summarizes and concludes.

4.2 Institutional background

This section first gives a brief overview of the Dutch health care system. Next, it describes the admission lotteries to medical school, and the study program to become a doctor.

4.2.1 Health care system in the Netherlands

Since the implementation of the Health Insurance Act in January 2006, all Dutch residents are legally obliged to purchase a basic health insurance package from private insurers.[58] Private insurers cannot reject applicants and are not allowed to charge different prices for the same package. In 2019, adults pay an annual community-rated premium of about 1200 euro. The government pays the premium for children under 18 years old and subsidizes individuals whose income is too low to afford the premium. The government collects an almost equal amount from general taxation which can be considered an income-dependent premium. These tax revenues are distributed among the private insurers on a risk-adjusted basis for their insured population (Kroneman et al., 2016).

The central government defines the content of the basic package. This covers medical care, including care provided by GPs, hospitals, specialists and midwives, and prescription drugs.[59] Every insured person over age 18 pays an annual deductible of 385

[58] The discussion in this subsection relies on Wammes et al. (2014).

[59] In addition, the basic care package covers dental care until age 18 (coverage after age 18 is confined to specialist dental care and dentures); medical aids and devices; maternity care; ambulance and patient transport services; paramedical care (limited physical/remedial therapy, speech therapy, occupational therapy, and dietary advice); basic ambulatory mental health care for mild to moderate mental disorders; and specialized outpatient and inpatient mental care for complicated and severe mental disorders.

euro (in 2019) for health-care costs,[60] including costs for hospital admission, medical transportation and prescription drugs but excluding costs for GP consultations, maternity care, home nursing care and care for children under the age of 18.[61] Voluntary supplemental health insurance is available for services not included in the basic health insurance package. In 2017, about 84 percent of all individuals had some form of supplemental health insurance, the most popular services being dental care, physiotherapy, glasses and contact lenses (Wammes et al., 2014).

The Netherlands spent 9.9 percent of its GDP on health care in 2018, which is similar to most other OECD countries but considerably lower than the health care expenditure of the US which in the same year amounted to 16.9 percent of its GDP (OECD, 2020*c*). Primary care is foremost provided by GPs who act as gatekeepers for access to hospital and specialist care. Only seven percent of contacts with a GP result in a referral to secondary care (Kroneman et al., 2016). With 3.3 doctors per 1000 inhabitants, the density of doctors in the Netherlands is similar to that in other OECD countries (OECD, 2020*a*).

4.2.2 The admission lotteries

Students who completed the academic track in secondary school in the Netherlands are eligible to enroll in all study programs at all Dutch universities.[62] Some study programs require that students have followed specific subjects at secondary schools, but programs are not allowed to select students based on grades or other student characteristics.[63] A number of study programs have quotas that limit how many students can be admitted. For medical school the quota was introduced in response to the drastically increasing

[60] People can reduce their insurance premium by taking additional deductibles up to 500 euros per year. These voluntary deductibles are not very popular, and particularly not among older individuals. In our sample of parents of medical school applicants, less than 7 percent have some additional deductible and there is no significant difference between parents of lottery winners and lottery losers.

[61] In addition to the deductible, individuals need to share some costs for selected services such as medical transportation via copayments, coinsurance or direct payments for services that are subsidized to a certain limit. A reimbursement limit is set for drugs in groups of equivalent drugs such that excess costs above this limit are not reimbursed.

[62] The information in this subsection largely follows Ketel et al. (2016).

[63] Graduating from secondary school requires an exam in seven subjects including Dutch and English. Applicants for medical school should also have passed biology, chemistry, physics and math. Once the exam is passed it cannot be retaken.

number of applicants at the end of the 1960s which exceeded the number of study places available.[64]

Until 1999, students who applied to medical school (and any other study program with a quota) were admitted on the basis of the results from a nationwide centralized lottery.[65] The lottery first determines which students can enroll in medical school and next distributes these students over the eight medical schools in the Netherlands. Based on their GPA on the secondary school exam, students are divided into categories, which determine students' weights in the admission lottery. Table 27 shows that students with a GPA exceeding 8.5 are in category A and they receive a weight of 2.00, while students with a GPA between 6 and 6.5 are assigned to category F with a weight of 0.67.[66] The category Other includes students who did not take the Dutch secondary school exams, e.g. foreign students, who will be excluded from our empirical analysis.

Rejected applicants are allowed to reapply in the next year, and until 1999 they could do this as often as they wanted. We observe that many but not all rejected first-time applicants reapplied at least once. This implies that admission to medical school is not only determined by lottery results. In our empirical analysis we will therefore use the result of the first lottery in which someone participated as instrumental variable for becoming a doctor.

4.2.3 The study program

During our observation period, the study program at medical school consisted of up to three phases (Ketel et al., 2016). In the first phase, students follow four years of fulltime medical education to receive their undergraduate diploma.[67] In the second phase, students receive two more years of on-the-job training which qualifies them for the basic degree, which is necessary to be included in the Dutch registry of health

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[64] See Goudappel (1999) for details on the reasons for introducing quotas.

[65] From 2000 onward, studies with quotas are allowed to admit (initially) at most 50 percent of the students using their own criteria. Universities have made increasing use of this and by now, the admission lotteries have been eliminated. Selection is often based on motivation and previous experience. For this reason we restrict our analysis to students who first applied for medical school before this change.

[66] The number of available places per lottery category is determined such that for the total number of available places divided by the number of applicants in a category, the weights hold.

[67] Like in other European countries, the structure of university education in the Netherlands is different from that in the US. Students immediately enter a specific field of study (such as medicine, law, or economics) and their entire curriculum is in that field.

Table 27: Lottery categories

Category	GPA	Weight	Share
A	$8.5 \leq \text{GPA} \leq 10$	2.00	1.7%
B	$8.0 \leq \text{GPA} < 8.5$	1.50	5.4%
C	$7.5 \leq \text{GPA} < 8.0$	1.25	8.6%
D	$7.0 \leq \text{GPA} < 7.5$	1.00	20.8%
E	$6.5 \leq \text{GPA} < 7.0$	0.80	22.1%
F	$6.0 \leq \text{GPA} < 6.5$	0.67	29.9%
Other	–	1.00	11.5%

Note: GPA describes the average of the student's final exam grades at secondary school. In the Netherlands, grades are between 1 and 10, with 5.5 and higher means passing. Weight is the weight in the admission lottery and Share describes the fraction of the applying students in each lottery category.

care professionals. This registration is required to enter the labor market for medical professionals. Less than 20 percent of those who enroll in medical school stop after the second phase and seek employment as *basisarts*. The vast majority continues to the third phase and enrolls in a specialization track, which commonly includes obtaining a PhD degree. The specialization tracks vary in duration ranging from three years for e.g. general practitioners to six years for, for example, surgeons and neurologists.

4.3 Data

This section describes the data used in the empirical analysis and provides summary statistics of the data.

4.3.1 Data sources and sample

We use administrative data from different registers available at Statistics Netherlands which can be linked at the individual level and at the parent-child level.[68]

The register on admission lotteries contains information on all applicants for medical school, their lottery category and the results in all lotteries. Lottery information is available for the years 1987 to 2004 (Statistics Netherlands, 2020*p*). To make sure that

[68] Individual-level demographic variables stem from the person registry (Statistics Netherlands, 2020*g*) and the household registry (Statistics Netherlands, 2020*e*). Children and parents can be linked using Statistics Netherlands (2020*m*).

we observe first-time applicants, we exclude applicants who participated in 1987 since we have no information about possible participation in 1986, and we exclude applicants older than 20 when we observe them applying for the first time. Because the lottery system was gradually abandoned after 1999, we exclude individuals applying for the first time after that year.[69]

From the lottery register we exclude applicants of whom at least one parent is registered as doctor in the register of health care professionals (Statistics Netherlands, 2020*c*), because for these parents having a child who is a doctor adds little medical expertise. This eliminates 12.9 percent of the applicants who won their first lottery and 12.2 percent of the applicants who lost their first lottery (p=0.083). The register of health care professionals was established in 1994 and mandated every health care professional to be registered in order to practice in the Netherlands.[70] We have information on actual study choices of all applicants and their study progress. For the lottery applicants we observe who enters the register and thus becomes a doctor.

About 90 percent of the fathers of the lottery applicants are born between 1934 and 1952, and 90 percent of the mothers were born between 1938 and 1954.[71] The mortality register contains all deaths from 1995 until 2019 (Statistics Netherlands, 2020*f*), so the oldest parents were in their late fifties when the mortality register started.

Data availability on health care use and health care costs varies because different data are provided by different institutions. We have access to health care costs that are reimbursed by the basic health insurance package (available from 2009 to 2017, Statistics Netherlands (2020*v*)), specialist visits and treatment costs (2013-2017, Statistics Netherlands (2020*r*)) and prescription medicine use coded according to the 4-digit Anatomical Therapeutic Chemical (ATC4) classification (2006-2017, Statistics Netherlands (2020*q*)). The register on prescription drugs covers medicine that is (partially) reimbursed by the statutory health insurance, but excludes drugs provided in hospitals

[69] We also drop applicants from lottery category A because only 68 applicants in this category lost the first lottery, 42 of them were admitted to medical school in the next year.

[70] We cannot identify parents with a medical degree who were never registered because they stopped working as health care professional before 1994. However, the oldest children were born in 1967 and if the parents worked until (early) retirement, then we might only miss parents who were in their very late thirties at the birth of their child. In robustness checks, we also exclude individuals where either parent is registered as nurse. This does not alter the conclusions.

[71] For 5.9 percent of the lottery applicants in our sample we can not link a father and for 3.0 percent we can not link a mother.

and nursing homes.[72] We use hospitalization records (1995-2017, Statistics Netherlands (2020*n,o*)) which comprise information on all hospital visits including those without overnight stay, main diagnosis according to the International Classification of Diseases (ICD9 and ICD10-classification) and some characteristics of the admitting hospital.[73]

Our measure of total annual costs comprises all health care costs covered by basic health insurance, which includes GP, pharmacy and hospital costs, costs for paramedical care, mental health care, geriatric rehabilitation, home care, patient transports, oral care, health care provided abroad and some other health care. Annual hospital costs include both inpatient and outpatient costs. Annual total, GP, pharmacy and hospital costs are from the data on reimbursements of the basic health insurance package, annual GP visit is also based on these data and equals one if there were positive GP consultation costs within a year. Specialist visit and treatment costs are from the records of diagnosis treatment combinations. Most specialist costs are also included in hospital costs of the basic health insurance package. All costs are converted to euros in 2015 and describe the combined spendings born by the insurer and the out-of-pocket payments of the patient. In the year that parents die we consider unadjusted health-care costs for that year.[74] Observations for the years after dying are ignored in the empirical analysis.

In addition to the sample of lottery participants, we also use the Statistics Netherlands register data to construct a sample from the general population containing all individuals born between 1967 and 1982 and their parents. We refer to this sample as the "full population". The children in this sample have the same birth years as the lottery participants. From this "full population" we construct a sample of college graduates and their parents. We refer to this sample as the "college graduates".[75] The "full population" and "college graduates" are used to determine associations between having a child who is a doctor and parents' mortality and health care use.[76]

[72]The records do not contain information on the quantity prescribed so that we only observe whether drugs from a specific ATC4 category were used in a year.

[73]Statistics Netherlands does not have outpatient records so that we can only identify parents having a specific disease or condition if the diagnosis was made in the hospital.

[74]Health care costs are highest just before dying, so annualizing costs for people who die early in the year would give extreme observations.

[75]In the Netherlands, individuals can obtain a college degree from a research university ("Wetenschappelijk Onderwijs", WO) or from a professional college ("Hoger Beroepsonderwijs", HBO).

[76]Information on educational attainment for the lottery applicants and "college graduates" is drawn from Statistics Netherlands (2020*i,j,k,l*).

4.3.2 Descriptive statistics

The upper panel in Table 28 reports summary statistics on study enrollment and completion by the result of the first lottery. Almost 94 percent of the applicants admitted to medical school in their first lottery actually enroll in the program. About 45 percent of the first-time lottery losers enroll in medical school after winning a subsequent lottery.[77] Almost all lottery winners enroll in a study program in the Netherlands, while about 96 percent of the losers do so. The share of lottery winners who complete medical school amounts to 82 percent, while the share among lottery losers is almost 41 percent. About 96 percent of lottery winners and 93 percent of lottery losers complete a study program in the Netherlands.

Table 28: Sample description by outcome of the first lottery

	Winners	Losers
Enrollment in medical school	93.8%	45.1%
Completion of medical school	82.4%	40.8%
Enrollment in a study program in NL	99.5%	96.3%
Completion of a study program in NL	96.1%	93.2%
Registration as doctor	80.6%	42.5%
Registered as GP	28.8%	30.9%
Registered as specialist	54.4%	51.9%
Registered without specialization	16.8%	17.2%
N	10,209	11,998

The bottom panel shows that almost all lottery winners that complete medical school also register as doctor. For lottery losers the fraction of licensed doctors is larger than the medical school completion rate. Some lottery losers complete medical school abroad (most likely Belgium) and then practice in the Netherlands. The lottery losers who complete medical school distribute themselves similarly as the lottery winners over the different types of doctors. About 30 percent of the doctors become GPs, about 53 percent register as specialist and about 17 percent either do not specialize or work as social doctor.[78]

[77] The reapplication rate among first-time lottery losers in category B is 81 percent. This rate decreases with lottery category, i.e. with the weight individuals receive in the lottery, to 67 percent in category F.

[78] Social doctors comprise, for instance, occupational health doctors, doctors for mentally disabled, community doctors, etc.

Table 29 shows that pre-treatment characteristics do not differ significantly between the parents of the winners and losers of the first lottery for medical school. The only exception is the 0.9 percentage point difference in the shares of parents being married or cohabiting in the pre-lottery year, which is significant at the 10% level.[79] Table A1 in online appendix A.1 shows balancing of pre-treatment characteristics of the applicants to medical school. None of the differences is significantly different from zero.

Table 29: Balancing of parental characteristics by outcome of the first medical school lottery application

	Lottery winners	Lottery losers	p-value
Fathers' annual income in 1999	56,713	57,059	0.54
Mothers' annual income in 1999	14,785	14,775	0.99
Annual parental income in 1999	67,666	68,415	0.37
Fathers' average annual income 1999-2003	53,739	53,906	0.69
Mothers' average annual income 1999-2003	15,186	15,234	0.83
Average annual parental income 1999-2003	64,981	65,706	0.35
Parents married/cohabiting pre-lottery year	86.8%	87.7%	0.07
Fathers' number of children	2.75	2.72	0.32
Mothers' number of children	2.70	2.68	0.45
Fathers' age at birth of applicant	30.5	30.5	0.68
Mothers' age at birth of applicant	28.3	28.3	0.84

Notes: Observations are weighted by the inverse probability of winning the lottery for each lottery category-lottery year combination to account for compositional differences between the two groups. The p-values in the final column are based on regressing the characteristics on an indicator for winning the first lottery and fixed effects for the lottery category interacted with the year of first application.

Table 30 lists the fields of study chosen by lottery losers who pursue another study in the Netherlands. The most popular alternative fields of study are within social sciences (Business and Economics, Psychology) and sciences (Science, Mathematics and Computing). Some lottery losers enroll in programs that have some health component (Nursing and Dentistry), but these programs yield considerably less medical knowledge than medical school and do not allow to practice medicine.

[79] Information on marriages and registered partnerships is drawn from Statistics Netherlands (2020*h*), information on cohabitation from Statistics Netherlands (2020*t*). Annual earnings are computed as sum of income from employment (Statistics Netherlands, 2020*b*), income from self-employment (Statistics Netherlands, 2020*u*), income from abroad (Statistics Netherlands, 2020*a*) and income from other sources (Statistics Netherlands, 2020*s*).

Table 30: Study fields of lottery losers (enrolled)

Field	Share
Business and Economics	12.5%
Science, Mathematics and Computing	10.7%
Psychology	10.0%
Health (e.g. Nursing, Dentistry)	8.8%
Law	8.3%
Pharmacy	7.9%
Health science, Movement science and Health care management	7.8%
Education	7.2%
Medical diagnostics and treatment techniques	6.7%
Engineering, Manufacturing and Construction	6.5%
Humanities and Arts	4.5%
Therapy and rehabilitation	3.3%
Others (Social sciences, Agriculture & Veterinary, Services, Welfare)	5.8%

4.4 Results

This section first reports OLS estimates of the correlation of having a child who is a doctor and parents' mortality and health care use in our three samples. Next, we exploit the admission lotteries for medical school to eliminate selection bias into the medical profession. This allows us to determine the causal effects of having a child who is a doctor on parents' mortality and health care use. Our main finding is that while the correlations are substantial, the causal effects show no evidence of large effects of having a child who is a doctor on parents' health care use and mortality.

4.4.1 Association of having a child who is a doctor with parental health outcomes

We first regress within the full population the different outcome variables of parents on whether their child is registered as doctor. In the OLS regressions, we control for gender and ethnicity of the child, fixed effects for the birth years of child and parent, and fixed effects for the years in which the outcome is observed. The sample is restricted to parents with children born between 1967 and 1982. We cluster standard errors at the level of the parent. The estimation results presented in the upper panel in Table

31 show that almost all outcome variables are more favorable for parents of doctors, and differences are always significant. The magnitudes of the estimated coefficients are very similar for fathers and mothers. Because it is very unlikely that we control for all relevant heterogeneity between parents of doctors and parents of non-doctors, the estimates should be interpreted as associations rather than causal effects.

Fathers of doctors are 7 percentage points less likely to have died by the end of 2019 compared to fathers of children not practicing as doctor, and this difference is 4.5 percentage points for mothers. The annual health care costs of parents of doctors are over 500 euros lower. These lower costs are due to lower costs for GP consultations, pharmaceuticals, hospital admissions and treatment by a specialist. The parents of doctors are less likely to visit a GP, to be prescribed any type of medication and to be hospitalized. They are, however, 0.8 to 1.0 percentage points more likely to visit a specialist.

The middle panel of Table 31 shows results when we restrict the sample to the parents of college graduates. The coefficients have the same sign as in the full sample, indicating that parents of doctors have more favorable outcomes than parents of other college graduates. However, the magnitudes of the estimates are smaller than in the full sample and some estimates are no longer significantly different from zero, particularly for mothers. The negative association of the child being a doctor with fathers' (mothers') mortality reduces to 2.8 (1.3) percentage points. The estimate for the difference in total health care costs declines to about 100 euros.

The bottom panel of Table 31 shows results when we restrict the sample to parents of lottery participants. Because there is substantial noncompliance with the outcome of the first lottery, these results have no causal interpretation. The resulting OLS estimates show that the differences in outcomes between parents of doctors and non-doctors decrease substantially compared to the results in both other panels and many of the estimates are not significantly different from zero. The negative association with parental mortality reduces further in magnitude compared to the estimates in the upper and middle panels. For GP costs we find that both fathers and mothers of doctors have significantly lower costs, but the effects are of economically negligible size. The change in results compared to the sample of college graduates shows that parents of lottery applicants differ from parents of other college graduates.

Table 31: Association of child being a doctor with parental mortality and health care access, use and costs

	Fathers			Mothers		
	Mean	$\hat{\beta}$	s.e	Mean	$\hat{\beta}$	s.e
Panel A. Full population						
Mortality (by 31.12.2019)	0.248	−0.070	(0.003)	0.139	−0.045	(0.002)
Total costs	4533	−547.64	(42.22)	3711	−523.52	(34.74)
GP visit (0/1)	0.838	−0.014	(0.002)	0.870	−0.013	(0.002)
GP costs	139	−21.92	(0.67)	141	−22.33	(0.65)
Specialist visit (0/1)	0.598	0.008	(0.003)	0.568	0.010	(0.003)
Specialist treatment costs	2228	−207.38	(36.12)	1694	−170.59	(30.29)
Any medication	0.836	−0.017	(0.002)	0.860	−0.013	(0.002)
Pharmacy costs	624	−91.47	(10.55)	551	−92.01	(9.08)
Hospitalization (0/1)	0.139	−0.013	(0.001)	0.129	−0.010	(0.001)
Hospital costs	2950	−274.18	(32.22)	2218	−227.84	(23.25)
N		3,057,971			3,220,845	
Panel B. College graduates						
Mortality (by 31.12.2019)	0.212	−0.028	(0.003)	0.113	−0.013	(0.002)
Total costs	4075	−132.25	(42.27)	3209	−72.13	(34.88)
GP visit	0.837	−0.012	(0.002)	0.866	−0.010	(0.002)
GP costs	127	−10.57	(0.67)	126	−8.96	(0.65)
Specialist visit (0/1)	0.599	0.011	(0.003)	0.565	0.016	(0.003)
Specialist treatment costs	2050	−35.84	(36.02)	1517	−0.79	(30.14)
Any medication	0.823	−0.002	(0.002)	0.843	0.002	(0.002)
Pharmacy costs	553	−24.17	(10.58)	459	−8.09	(9.15)
Hospitalization (0/1)	0.129	−0.002	(0.001)	0.116	0.002	(0.001)
Hospital costs	2680	−39.08	(32.26)	1967	−11.44	(23.34)
N		950,881			985,496	
Panel C. Medicine lottery participants						
Mortality (by 31.12.2019)	0.191	−0.009	(0.005)	0.105	−0.010	(0.004)
Total costs	3986	−52.18	(80.53)	3173	−50.69	(64.71)
GP visit	0.830	−0.011	(0.003)	0.859	−0.005	(0.003)
GP costs	119	−6.00	(1.25)	120	−5.91	(1.23)
Specialist visit (0/1)	0.607	0.016	(0.005)	0.582	0.002	(0.005)
Specialist treatment costs	2044	17.54	(63.76)	1533	29.84	(47.50)
Any medication	0.822	0.006	(0.004)	0.845	0.010	(0.003)
Pharmacy costs	539	−24.14	(22.62)	459	2.39	(16.70)
Hospitalization (0/1)	0.127	0.002	(0.002)	0.116	0.002	(0.002)
Hospital costs	2652	6.86	(60.87)	1963	−25.45	(44.09)
N		20,900			21,547	

Notes: Cluster-robust standard errors in parentheses. All regressions include controls for gender and ethnicity of the child, fixed effects for the child's and parent's year of birth, and fixed effects for the year the outcome is observed. All costs are converted to euros in 2015. The means in panels A and B are weighted to mirror the age distribution of medical school applicants.

4.4.2 Causal evidence from admission lotteries

Within the full population, parents of doctors have lower mortality and lower health care use and costs than parents of non-doctors. A substantial part of this difference is due to selection. Restricting the control group to parents of non-doctors who are more similar to the doctors reduces the differences. Still, even in the sample of lottery participants doctors are not a random subsample due to noncompliance with the outcome of the first admission lottery. In this subsection, we use an instrumental variables approach to deal with this noncompliance and recover causal effects of the child being a doctor on parents' mortality and health care use and costs.

Empirical approach and first-stage results

We are interested in the effects of being a doctor on parental mortality, health care use and costs. We assume a linear relationship between outcome variable Y in year t of individual i's parent (Y_{it}), and being a doctor (D_i):

$$Y_{it} = \alpha_t + \delta D_i + X_i\beta + LC_i + U_{it} \tag{4.1}$$

The effect of being a doctor on outcomes is captured by δ, the parameter of interest. The vector of controls X_i includes a linear term for applicant's age at first lottery participation[80], a gender dummy, an indicator for non-western origin and fixed effects for the birth years of child and parent. The interaction term between the lottery category and year of first participation, LC_i, controls for the fact that individuals' chances of being admitted are only identical conditional on lottery year and category. Lastly, α_t are fixed effects for the year in which the outcome is observed and U_{it} is an individual-specific error term.[81] When estimating the effect on mortality, Y is an indicator equal to one if the parent died before the end of the observation period, and zero otherwise. Subscript t is then dropped and α is an intercept rather than a fixed calendar time effect.[82]

[80] Age is measured as a continuous variable in years based on exact birth dates.

[81] Less than 5% of the parents have more than one child participating in the lottery. In our main analysis, these parents appear twice and we correct for this by clustering standard errors at the parent level. The alternative is to exclude families with siblings participating in the admission lottery or to only consider the oldest sibling we observe in our sample. In both cases, the general pattern is that p-values increase.

[82] Most outcome variables are available from 2006 or later onwards (see Subsection 4.3.1) which is at least six years after participation in the first lottery (recall that we limit the sample to parents of

Compliance with the result of the first admission lottery is imperfect (see Subsection 4.3.2). Not all winners of the first lottery enroll in medical school, and some drop out before completing their degree and being registered as a doctor. A substantial fraction of lottery losers reapply in subsequent years and eventually become a doctor. To deal with the endogeneity of becoming a doctor, we use the result of the first admission lottery in which the applicant participated (LR_{1i}) as instrumental variable:

$$D_i = \kappa + \lambda LR_{1i} + X_i\theta + LC_i + V_i \tag{4.2}$$

All applicants to medical school participate at least once in an admission lottery, so there is no sample selection when considering the outcome of the first admission lottery. Conditional on the lottery category interacted with the year of the first application, the outcome of the first lottery is random. This ensures that the independence assumption underlying the instrumental variable approach is satisfied: $E[U_{it}|X_i, LC_i, LR_{1i}] = E[U_{it}|X_i, LC_i]$. This is supported by the balancing shown in Table 29 and online appendix Table A1. The parameter λ describes the fraction of compliers in the sample. In our setting compliers are individuals for whom the result of the first lottery determines whether they ever become a doctor. The treatment effect δ in equation (4.1) should be interpreted as Local Average Treatment Effect (LATE).

We run the first-stage regressions separately for fathers and mothers. The estimates for λ are in panel A of Table 32 and show that the outcome of the first admission lottery is a strong instrument. The F-statistics are above 3000. Winning the first lottery increases the probability to become a doctor by 36 percentage points. Because lottery losers may opt for other health-related fields of study or register as another type of health-care professional, we consider two alternative first-stage regressions. Panel B shows that winning the first lottery increases the probability to enroll in any health-related field of study with 25 percentage points. Panel C shows that the probability to be registered in the Dutch registry of health-care professionals, which comprises doctors, nurses, dentists, pharmacists, midwifes, physician assistants and physiotherapists increases with about 30 percentage points for both parents.[83] Both alternative first-stages yield somewhat smaller estimates, but they remain sizable and highly significant.

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medical school applicants in the years 1988 to 1999). The exception are outcome variables retrieved from hospitalization records which are available from 1995 onwards. For analyses based on these records, we include parents in the sample from six years after the first lottery in which their child participated

Table 32: First-stage estimates

	Mean	$\hat{\lambda}$	s.e.	F-statistic	N
Panel A. Child being a doctor					
Fathers	0.429	0.359	(0.007)	3030.4	20,900
Mothers	0.428	0.359	(0.006)	3128.8	21,547
Panel B. Child enrolled in a health field					
Fathers	0.622	0.253	(0.006)	1847.2	20,900
Mothers	0.620	0.253	(0.006)	1895.0	21,547
Panel C. Child registered as health-care professional					
Fathers	0.521	0.296	(0.006)	2168.0	20,900
Mothers	0.519	0.296	(0.006)	2215.8	21,547

Notes: Cluster-robust standard errors in parentheses. All specifications include controls for gender, ethnicity, age at the first lottery application, fixed effects of the birth year of the applicant and parent, and fixed effects for the lottery category interacted with the year of first lottery.

Parental mortality

Panel A in Table 33 reports the estimated causal effects of having a child who is a doctor on fathers' and mothers' probability of having died by the end of 2019. The IV estimates are small and not significantly different from zero, implying that a child who is a doctor does not prolong parents' life. The IV estimates are only around five percent of the earlier reported full population correlations. Taken the size of the standard errors into account, we can rule out with 95% probability effects on mortality larger than half the size of the conditional correlations found in the full population (cf. Table 31). The results are robust to restricting the sample to parents born before 1945 and considering mortality as having died before the age of 75.

Rather than having died at a given moment in time or before a particular age, we can consider the age of dying using duration models. For this purpose, we use a Cox proportional hazard model on the reduced form, i.e. we use the result of the first lottery as regressor rather than being a doctor.[84] The hazard rate model includes the same

onwards.

[83]The registry also includes psychologists and psychotherapists, which we do not consider as health professions as they belong to the field of social science. Including these would slightly reduce the estimates to 0.279.

[84]Instrumental variable approaches do not combine easily with (non-linear) hazard rate models.

Table 33: Effects on parental mortality

Panel A. Effect on parent died by 31-12-2019; IV estimates					
	Complier mean	$\hat{\delta}_{IV}$	s.e.	p-value	N
Full sample					
Fathers	0.1708	−0.0042	(0.0151)	0.779	20,900
Mothers	0.0965	0.0004	(0.0122)	0.976	21,547
Parents born before 1945					
Fathers	0.1732	0.0115	(0.0251)	0.645	8620
Mothers	0.1035	0.0020	(0.0252)	0.937	5948
Panel B. Effect on hazard rate; Cox proportional hazard model					
	Baseline hazard	$\hat{\beta}_{Cox}$	s.e.	p-value	N
Full sample					
Fathers	0.0149	0.0058	(0.0340)	0.864	20,900
Mothers	0.0083	0.0110	(0.0456)	0.809	21,547
Parents born before 1945					
Fathers	0.0193	0.0333	(0.0552)	0.547	8620
Mothers	0.0108	0.0126	(0.0869)	0.885	5948
Panel C. Equality of survivor functions; Wilcoxon rank-sum tests					
		χ^2		p-value	N
Full sample					
Fathers		0.00		0.980	20,900
Mothers		0.45		0.504	21,547
Parents born before 1945					
Fathers		1.34		0.248	8620
Mothers		0.02		0.894	5948

Notes: Cluster-robust standard errors in parentheses. All specifications include controls for gender, ethnicity, age at the first lottery application, fixed effects of the birth year of the applicant and parent, and fixed effects for the lottery category interacted with the year of first lottery. The rank-sum tests in panel C control for differences in admission probabilities by lottery categories in the different years.

regressors and fixed effects as the linear regression model discussed above. Panel B in Table 33 presents the marginal effects. It shows estimates on the full sample and on the restricted sample of parents born before 1945 (potentially reaching at least age 75 during the observation period), respectively. The effects are small and not significantly different from zero.

Finally, we conduct Wilcoxon rank-sum tests for equality of the survivor functions between the parents of the lottery losers and the parents of the lottery winners to investigate whether there are differences at other points in the distribution. In these rank-sum tests we control for the lottery category interacted with the year of the first lottery. As shown in panel C, in no case can we reject the null hypothesis of equality of the survivor functions of lottery winners' and losers' parents. So all three tests show that whether or not the child is a doctor does not affect the longevity of parents.

Parental health care use and costs

Table 34 shows the IV estimates on health care use and costs, separately for fathers (panel A) and mothers (panel B). For fathers we find no significant effect on total health care costs, while for mothers the effect on total health care costs is positive, equals 326 euros (11% of the control complier mean) and is significant at the 10%-level. Taking the size of the standard errors into account, the IV estimates for total health care costs, rule out with 95% probability effect sizes as large as 72% (for fathers) and 11% (for mothers) of the conditional correlations for the full population as reported in Table 31. Note that these correlations and the IV estimates have opposite signs.

When looking at separate components of health care use and costs, we see small but marginally significant positive effects on the probability to visit a specialist for fathers and on the probabilities of hospitalization for fathers and mothers. We find no significant effects on any of the separate cost components. The estimates on specialist treatment and hospital costs are, however, not very precise so that substantial effects cannot be ruled out. Again the point estimates of the effects on the cost components have the opposite signs of the conditional correlations reported in Table 31.

Because we consider many outcomes, we also report significance levels that correct for multiple hypotheses testing. We follow the approach suggested by Anderson (2008) and compute false-discovery-rate adjusted p-values referred to as FDR q-values. Anderson (2008) shows that the FDR q-values are less conservative than the Bonferroni correction. We compute the FDR q-values for two groups separately, i.e. the cost factors (GP costs, specialist treatment costs, pharmacy costs and hospital costs) and the health care use indicators (GP visit, specialist visit, any medication and hospitalization). The estimates that were significantly different from zero at the 10% level without a correction, are no longer significantly different from zero based on the FDR q-values.

Table 34: IV estimates of the effects of being a doctor on parental health care use and costs

	Complier mean	$\hat{\delta}$	s.e.	p-value	FDR q-value
Panel A. Fathers					
Total costs	3832.01	64.23	(229.49)	0.780	-
GP visit	0.8299	-0.0137	(0.0091)	0.134	0.179
GP costs	118.86	-4.68	(3.58)	0.191	0.511
Specialist visit (0/1)	0.5809	0.0282	(0.0151)	0.061	0.123
Specialist treatment costs	1851.58	203.16	(178.60)	0.255	0.511
Any medication	0.8151	0.0030	(0.0110)	0.783	0.783
Pharmacy costs	585.20	-25.75	(56.07)	0.646	0.647
Hospitalization (0/1)	0.1349	0.0108	(0.0054)	0.046	0.123
Hospital costs	2464.35	95.14	(173.76)	0.584	0.647
Panel B. Mothers					
Total costs	2922.94	326.45	(192.21)	0.089	-
GP visit	0.8592	-0.0023	(0.0084)	0.787	0.787
GP costs	119.33	-3.06	(3.46)	0.377	0.377
Specialist visit (0/1)	0.5745	0.0050	(0.0144)	0.727	0.787
Specialist treatment costs	1458.67	172.39	(154.10)	0.263	0.377
Any medication	0.8373	0.0110	(0.0098)	0.264	0.529
Pharmacy costs	415.90	45.98	(51.68)	0.374	0.377
Hospitalization (0/1)	0.1255	0.0092	(0.0052)	0.079	0.317
Hospital costs	1844.97	179.99	(133.05)	0.176	0.377

Notes: Cluster-robust standard errors in parentheses. FDR q-values are false-discovery-rate adjusted p-values following Anderson (2008). The FDR q-values are computed separately for fathers and mothers, and for two groups, use indicators (GP visit, specialist visit, any medication, hospitalization) and cost factors (GP costs, specialist treatment costs, pharmacy costs, hospital costs). All specifications include controls for gender, ethnicity, age at the first lottery application, fixed effects of the birth year of the applicant and parent, and fixed effects for the lottery category interacted with the year of first lottery.

The estimates in Table 34 consider broad categories of health care use and costs. In online appendix A.2 we show estimates for finer measures of health care use. We consider the type of specialist visited by the parent (Table A2), the characteristics of the hospital visit and the main diagnosis made in hospital (Table A3), and the type of medication use (Table A4). We do not find effects on the characteristics of the hospital visit (duration, acute admission, top clinical or university medical center) at the 5%-level, but there are a few significant effects for the type of treating specialist, hospital diagnosis and type of medication. When we adjust for multiple hypotheses testing, the only estimate that remains significant is that mothers of doctors are more likely to be diagnosed with a heart failure in the hospital, which is a rare event. Overall, the estimates do not indicate that doctors have a substantial effect on the health care use of their parents.

We performed three heterogeneity analyses. We find some evidence that the few significant effects in Table 34 are due to daughters and not to sons (see online appendix Table A5). Second, we divide the applicant sample by lottery category. To get sufficient power, we group those in categories B, C and D and those in categories E and F (see online appendix Table A6). There are only minor differences in favor of categories E and F (students with lower high school GPA). Third, we consider the distance between the homes of the parent and the child.[85] We split the sample in more or less than 40 kilometers travel distance. Effects are not larger if the distance is shorter (see online appendix Table A7).

Our findings differ from those of Chen et al. (2019), who find favorable effects of being a doctor on health outcomes of relatives in Sweden. The authors use admission lotteries that were conducted when too many applicants had the maximum GPA from high school, which is normally used for admission. The results of the lottery-based analyses are complemented with results from an event study design in which health outcomes of relatives of doctors are compared to health outcomes of relatives of lawyers.

There are several possible explanations for the different findings in the two studies. First, lottery participants in Sweden are students with the maximum high school GPA, while our analysis excludes students with the highest GPA's because too few of them lost an admission lottery. Heterogeneous effects between top students and other students could then (partially) explain the different results.[86] Second, it may be that in the Netherlands a larger fraction of lottery losers ends up in a health-related study or profession than in Sweden. This would dampen the effect of a doctor in the family in

[85] Individuals' addresses are obtained from Statistics Netherlands (2020*d*).

[86] As we mentioned in footnote 69, there are too few (complying) lottery losers in top category A to obtain meaningful estimates for this group.

the Netherlands more than in Sweden. Third, the Netherlands is a small and densely populated country where most people live close to a doctor or hospital. This may reduce the importance of a relative with medical knowledge compared to Sweden which is much larger and more sparsely populated. While some of our results (no heterogeneous effects by grouped lottery categories or by distance between homes of parent and child, and sizable and significant first stages on health-related study or profession) lend no support to these explanations, we cannot rule them out entirely. Finally, the data from Sweden contain information that is not included in our data, such as diagnoses for specialist outpatient visits outside of primary care and more detailed drug prescription data (ATC5-classification instead of ATC4). This allows them to focus on drug prescription conditional on being diagnosed. We have mortality and health care costs as main outcomes, which are not considered by Chen et al. (2019) in their lottery-based analysis.

Following Chen et al. (2019) we also conducted an event study analysis in which we compare mortality and health care use and costs between the parents of doctors and the parents of lawyers. Online appendix B describes the analysis and reports the results. When considering the same outcomes as Chen et al. (2019) we obtain similar results. The results point to negative effects of having a child who is a doctor on parents' mortality and total health care costs, no significant effects on hospitalization and positive effects on medication use of mothers. One interpretation of the different findings from the lottery-based analysis and the event-study analysis is that the latter does not fully eliminate selection bias in the Dutch setting. Alternatively, we can regard the estimates from the two designs as different causal effects. The lottery design identifies the effect of the child being a doctor versus the second-best profession, whereas the event-study design identifies the effect of the child being a doctor versus being a lawyer. It can be argued that both effects capture differences in access to the health care system, but that the event-study estimates capture a larger gap in medical information than the lottery-based estimates.[87]

[87]We thank an anonymous referee for this suggestion.

4.5 Conclusion

A large literature shows that even in the presence of universal health insurance coverage there remains inequality in access to health care. It is often argued that information limitations about health conditions and the health care system and differences in the capability to communicate with medical professionals are relevant drivers of this inequality. We test the importance of these mechanisms by investigating if mortality and health care use of parents are affected by whether or not their child is a doctor.

We document that parents have lower mortality rates and lower health care costs when their child is a doctor. When restricting the population to parents of college graduates, differences become smaller, but remain significant. Because doctors are not a random subsample of all college graduates, these differences are likely to suffer from selection bias. To estimate causal effects, we exploit admission lotteries to medical school that took place between 1988 and 1999 in the Netherlands.

Our data contain a large range of variables describing health care use and costs. During our observation period, the majority of the parents of the lottery applicants were between 65 and 80 years old and thus in a phase in which health care use is substantial and mortality not negligible. Our findings show that having a child who is a doctor has no impact on parents' longevity, while effects on parents' health care use and costs are mostly not significantly different from zero. The results do not change when splitting the sample by gender of the child or by the distance between the homes of parent and child. The associations we find for the general population and the population of college graduates are thus driven by selection.

Our results imply that there are no important spillovers from the medical expertise and connections from doctors to their parents. This suggests that the health care system provides high-quality health care and information to all parents. We should stress, however, that our results apply to parents of individuals who applied for medical school, so these parents have relatively high-educated children. Therefore, our results are not conclusive about equality of health care access in the Netherlands in general.

4.6 Appendix

4.6.1 Additional tables

Balancing tests

Table 35: Balancing of applicants' characteristics by outcome of the first medical school lottery application

	Lottery winners		Lottery losers	p-value
Lottery category B				
Female	60.1%		62.3%	0.33
Age at first application	18.0		17.9	0.58
Non-Western immigrant	5.3%		4.6%	0.83
N		1542		
Lottery category C				
Female	63.1%		64.1%	0.40
Age at first application	18.0		18.0	0.11
Non-Western immigrant	4.3%		4.3%	0.65
N		2359		
Lottery category D				
Female	60.0%		61.4%	0.31
Age at first application	18.2		18.2	0.91
Non-Western immigrant	5.8%		5.9%	0.75
N		5315		
Lottery category E				
Female	58.7%		60.4%	0.20
Age at first application	18.4		18.3	0.18
Non-Western immigrant	8.2%		7.8%	0.23
N		5604		
Lottery category F				
Female	56.9%		57.3%	0.59
Age at first application	18.6		18.5	0.07
Non-Western immigrant	11.7%		11.2%	0.20
N		7387		

Notes: The p-values in the final column are weighted by the admittance probabilities for students in different years of lottery application.

IV-estimates for specific types of health care use

Table 36: IV-estimates of the effects of being a doctor on parental specialist visits

	Complier mean	$\hat{\delta}$	s.e.	p-value	FDR q-value
Panel A. Fathers					
Surgery	0.0876	0.0101	(0.0080)	0.206	0.503
Neurosurgery	0.0082	0.0044	(0.0027)	0.102	0.441
Gastroenterology	0.0525	0.0006	(0.0062)	0.919	0.920
Lung specialist	0.0574	0.0064	(0.0075)	0.395	0.643
Internal medicine	0.1170	−0.0027	(0.0106)	0.797	0.890
Cardiology	0.1718	0.0120	(0.0132)	0.362	0.643
Neurology	0.0771	0.0023	(0.0076)	0.760	0.890
Rheumatology	0.0223	0.0019	(0.0053)	0.724	0.890
Geriatrics	0.0118	0.0048	(0.0027)	0.082	0.441
Ophthalmology	0.1546	−0.0132	(0.0111)	0.232	0.503
Ear, nose & throat	0.0680	0.0016	(0.0069)	0.821	0.890
Orthopedics	0.0599	0.0096	(0.0069)	0.162	0.503
Dermatology	0.1111	0.0227	(0.0102)	0.026	0.343
Panel B. Mothers					
Surgery	0.1174	−0.0044	(0.0087)	0.615	0.875
Neurosurgery	0.0081	0.0004	(0.0023)	0.874	0.875
Gastroenterology	0.0536	0.0128	(0.0061)	0.034	0.440
Lung specialist	0.0514	−0.0012	(0.0065)	0.849	0.875
Internal medicine	0.1131	0.0102	(0.0100)	0.311	0.875
Cardiology	0.1031	0.0084	(0.0094)	0.374	0.875
Neurology	0.0730	−0.0025	(0.0066)	0.706	0.875
Rheumatology	0.0373	0.0043	(0.0062)	0.493	0.875
Geriatrics	0.0083	0.0008	(0.0020)	0.695	0.875
Ophthalmology	0.1536	0.0157	(0.0108)	0.147	0.875
Ear, nose & throat	0.0536	0.0041	(0.0061)	0.503	0.875
Orthopedics	0.1003	−0.0018	(0.0080)	0.820	0.875
Dermatology	0.1030	0.0113	(0.0095)	0.232	0.875

Notes: Cluster-robust standard errors in parentheses. FDR q-values are false-discovery-rate adjusted p-values following Anderson (2008). The FDR q-values are computed separately for fathers and mothers. All specifications include controls for gender, ethnicity, age at the first lottery application, fixed effects of the birth year of the applicant and parent, and fixed effects for the lottery category interacted with the year of first lottery.

Table 37: IV-estimates of the effects of being a doctor on parental hospitalizations

	Complier mean	$\hat{\delta}$	s.e.	p-value	FDR q-value
Panel A. Fathers					
Hospital stay					
Duration hospitalization	0.0030	0.0000	(0.0002)	0.848	0.849
Acute admission	0.0479	0.0021	(0.0029)	0.479	0.639
Top clinical	0.0597	0.0073	(0.0040)	0.070	0.238
University medical center	0.0243	0.0040	(0.0026)	0.119	0.238
Main diagnosis					
Respiratory diseases	0.0075	−0.0002	(0.0011)	0.833	0.833
Abdominal hernia	0.0076	−0.0008	(0.0009)	0.395	0.833
Cholelthiasis & cholecystitis	0.0018	0.0001	(0.0004)	0.773	0.833
Lung cancer	0.0025	0.0001	(0.0005)	0.784	0.833
Prostate cancer	0.0024	0.0013	(0.0006)	0.044	0.175
Cancers	0.0192	0.0044	(0.0017)	0.010	0.122
Liver cirrhosis	0.00002	−0.0004	(0.0002)	0.038	0.175
Circulatory diseases	0.0290	−0.0010	(0.0025)	0.675	0.833
Hypert. & cerebrovasc. dis.	0.0030	0.0006	(0.0007)	0.377	0.833
Heart failure	0.0014	0.0001	(0.0005)	0.769	0.833
Heart attack	0.0035	−0.0002	(0.0006)	0.700	0.833
Other ischemic heart dis.	0.0083	−0.0005	(0.0013)	0.680	0.833
Panel B. Mothers					
Hospital stay					
Duration hospitalization	0.0021	0.0003	(0.0002)	0.073	0.262
Acute admission	0.0314	0.0035	(0.0023)	0.131	0.262
Top clinical	0.0514	0.0030	(0.0036)	0.403	0.538
University medical center	0.0194	0.0000	(0.0022)	0.999	0.999
Main diagnosis					
Respiratory diseases	0.0056	−0.0002	(0.0008)	0.769	0.951
Abdominal hernia	0.0012	0.0001	(0.0004)	0.871	0.951
Cholelthiasis & cholecystitis	0.0021	−0.0004	(0.0005)	0.436	0.754
Lung cancer	0.0014	−0.0001	(0.0003)	0.661	0.951
Breast cancer	0.0042	−0.0005	(0.0006)	0.440	0.754
Cancers	0.0185	−0.0001	(0.0016)	0.974	0.974
Liver cirrhosis	0.0002	0.0000	(0.0002)	0.833	0.951
Circulatory diseases	0.0135	0.0026	(0.0016)	0.113	0.610
Hypert. & cerebrovasc. dis.	0.0022	−0.0005	(0.0006)	0.407	0.754
Heart failure	0.0001	0.0008	(0.0003)	0.003	0.042
Heart attack	0.0006	0.0004	(0.0003)	0.203	0.610
Other ischemic heart dis.	0.0025	0.0009	(0.0007)	0.171	0.610

Notes: Cluster-robust standard errors in parentheses. FDR q-values are false-discovery-rate adjusted p-values following Anderson (2008). The FDR q-values are computed separately for fathers and mothers, and for two groups, characteristics of the hospital stay and main diagnosis. All specifications include controls for gender, ethnicity, age at the first lottery application, fixed effects of the birth year of the applicant and parent, and fixed effects for the lottery category interacted with the year of first lottery.

Table 38: IV-estimates of the effects of being a doctor on parental medicine use

	Complier mean	$\hat{\delta}$	s.e.	p-value	FDR q-value
Panel A. Fathers					
Peptic ulcer med.	0.1943	0.0237	(0.0130)	0.069	0.390
Diabetes medication	0.0899	−0.0104	(0.0108)	0.338	0.820
Antithrombotic agents	0.2505	0.0030	(0.0158)	0.851	0.952
Diuretics	0.1179	−0.0065	(0.0106)	0.540	0.876
Beta-blocking agents	0.1917	0.0009	(0.0145)	0.948	0.952
Lipid-modifying agents	0.2772	−0.0010	(0.0169)	0.952	0.952
Corticosteroids	0.1498	0.0091	(0.0091)	0.318	0.820
Penicillins	0.1326	0.0018	(0.0063)	0.775	0.952
Anti-inflamm./anti-rheum. med.	0.1643	0.0251	(0.0085)	0.003	0.053
Opioids	0.0538	0.0090	(0.0046)	0.052	0.390
Psycholeptics	0.0592	0.0009	(0.0057)	0.876	0.952
Antidepressants	0.0461	0.0042	(0.0074)	0.567	0.876
Dementia medication	0.0048	−0.0022	(0.0018)	0.206	0.820
Nasal preparations	0.0933	−0.0071	(0.0087)	0.415	0.820
Obstructive airway disease med.	0.0983	0.0077	(0.0099)	0.434	0.820
Antihistamines	0.0549	0.0012	(0.0067)	0.856	0.952
Anti-infectives	0.0437	−0.0029	(0.0036)	0.422	0.820
Panel B. Mothers					
Peptic ulcer med.	0.2273	0.0234	(0.0130)	0.072	0.244
Diabetes medication	0.0474	0.0205	(0.0084)	0.015	0.128
Antithrombotic agents	0.1308	0.0062	(0.0112)	0.583	0.788
Diuretics	0.1164	0.0122	(0.0109)	0.265	0.564
Beta-blocking agents	0.1683	−0.0069	(0.0134)	0.607	0.788
Lipid-modifying agents	0.1795	0.0159	(0.0137)	0.246	0.564
Corticosteroids	0.1517	0.0065	(0.0086)	0.452	0.768
Penicillins	0.1355	0.0049	(0.0064)	0.446	0.768
Anti-inflamm./anti-rheum. med.	0.2135	0.0031	(0.0091)	0.731	0.828
Opioids	0.0694	−0.0035	(0.0056)	0.526	0.788
Psycholeptics	0.0835	0.0011	(0.0070)	0.872	0.873
Antidepressants	0.0944	0.0019	(0.0099)	0.847	0.873
Dementia medication	0.0042	−0.0024	(0.0013)	0.063	0.244
Nasal preparations	0.0996	0.0192	(0.0089)	0.031	0.178
Obstructive airway disease med.	0.0968	0.0248	(0.0100)	0.014	0.128
Antihistamines	0.0804	0.0109	(0.0082)	0.182	0.517
Anti-infectives	0.0522	−0.0018	(0.0039)	0.648	0.788

Notes: Cluster-robust standard errors in parentheses. FDR q-values are false-discovery-rate adjusted p-values following Anderson (2008). The FDR q-values are computed separately for fathers and mothers. All specifications include controls for gender, ethnicity, age at the first lottery application, fixed effects of the birth year of the applicant and parent, and fixed effects for the lottery category interacted with the year of first lottery.

Heterogeneity analysis

Table 39: IV-estimates of the effects of being a doctor on parental health care by gender of the child

	Sons				Daughters			
	$\hat{\delta}$	s.e.	p-value	FDR q-value	$\hat{\delta}$	s.e.	p-value	FDR q-value
Panel A. Fathers								
Mortality (by 31.12.2019)	-0.0015	(0.0229)	0.948	-	-0.0058	(0.0200)	0.773	-
Total costs	218.46	(373.86)	0.559	-	-59.11	(288.70)	0.838	-
GP visit	-0.0094	(0.0137)	0.491	0.966	-0.0168	(0.0123)	0.170	0.228
GP costs	-4.87	(5.40)	0.367	0.368	-4.86	(4.77)	0.308	0.797
Specialist visit (0/1)	-0.0010	(0.0227)	0.966	0.966	0.0508	(0.0202)	0.012	0.049
Specialist treatment costs	702.14	(398.99)	0.078	0.314	-52.75	(204.40)	0.796	0.797
Any medication	0.0010	(0.0163)	0.951	0.966	0.0058	(0.0149)	0.695	0.696
Pharmacy costs	-106.99	(99.48)	0.282	0.368	38.30	(64.75)	0.554	0.797
Hospitalization (0/1)	0.0041	(0.0083)	0.623	0.966	0.0159	(0.0073)	0.028	0.057
Hospital costs	307.35	(285.53)	0.282	0.368	-60.06	(217.23)	0.782	0.797
Panel B. Mothers								
Mortality (by 31.12.2019)	0.0026	(0.0184)	0.886	-	-0.0008	(0.0161)	0.960	-
Total costs	280.59	(298.71)	0.348	-	372.38	(253.53)	0.142	-
GP visit	-0.0235	(0.0126)	0.063	0.252	0.0129	(0.0112)	0.248	0.331
GP costs	-7.64	(5.40)	0.157	0.627	0.93	(4.61)	0.841	0.841
Specialist visit (0/1)	-0.0083	(0.0219)	0.707	0.775	0.0180	(0.0192)	0.349	0.350
Specialist treatment costs	-136.77	(176.23)	0.438	0.666	421.10	(243.38)	0.084	0.335
Any medication	-0.0065	(0.0145)	0.657	0.775	0.0240	(0.0133)	0.072	0.145
Pharmacy costs	30.53	(71.13)	0.668	0.668	60.19	(72.79)	0.408	0.545
Hospitalization (0/1)	0.0023	(0.0081)	0.774	0.775	0.0154	(0.0069)	0.026	0.104
Hospital costs	136.48	(202.06)	0.499	0.666	215.97	(178.78)	0.227	0.455

Notes: Cluster-robust standard errors in parentheses. FDR q-values are false-discovery-rate adjusted p-values following Anderson (2008). The FDR q-values are computed separately for the four parent-child pairs and within these groups for two subgroups, use indicators (GP visit, specialist visit, any medication, hospitalization) and cost factors (GP costs, specialist treatment costs, pharmacy costs, hospital costs). All specifications include controls for ethnicity, age at the first lottery application, fixed effects of the birth year of the applicant and parent, and fixed effects for the lottery category interacted with the year of first lottery.

Table 40: IV-estimates of the effects of being a doctor on parental health care by lottery category of the child

	Categories B, C & D				Categories E & F			
	$\hat{\delta}$	s.e.	p-value	FDR q-value	$\hat{\delta}$	s.e.	p-value	FDR q-value
Panel A. Fathers								
Mortality (by 31.12.2019)	-0.0237	(0.0261)	0.364	-	0.0086	(0.0186)	0.645	-
Total costs	149.41	(387.65)	0.700	-	31.41	(287.94)	0.913	-
GP visit	-0.0192	(0.0164)	0.240	0.439	-0.0092	(0.0110)	0.403	0.404
GP costs	-2.11	(6.12)	0.730	0.764	-6.35	(4.37)	0.146	0.459
Specialist visit (0/1)	0.0209	(0.0269)	0.438	0.439	0.0353	(0.0182)	0.052	0.209
Specialist treatment costs	134.44	(279.38)	0.630	0.764	239.18	(229.97)	0.298	0.459
Any medication	-0.0167	(0.0204)	0.413	0.439	0.0145	(0.0129)	0.263	0.351
Pharmacy costs	61.99	(99.99)	0.535	0.764	-65.81	(69.50)	0.344	0.459
Hospitalization (0/1)	0.0117	(0.0095)	0.219	0.439	0.0096	(0.0067)	0.148	0.297
Hospital costs	88.86	(295.96)	0.764	0.764	102.30	(217.30)	0.638	0.638
Panel B. Mothers								
Mortality (by 31.12.2019)	0.0164	(0.0210)	0.436	-	-0.0088	(0.0149)	0.554	-
Total costs	68.24	(302.29)	0.821	-	486.74	(245.05)	0.047	-
GP visit	-0.0183	(0.0152)	0.228	0.671	0.0047	(0.0100)	0.639	0.640
GP costs	-9.02	(5.97)	0.131	0.525	0.10	(4.26)	0.982	0.983
Specialist visit (0/1)	-0.0119	(0.0259)	0.647	0.863	0.0144	(0.0172)	0.402	0.536
Specialist treatment costs	163.55	(193.34)	0.398	0.564	201.33	(227.91)	0.377	0.503
Any medication	-0.0177	(0.0184)	0.335	0.671	0.0255	(0.0114)	0.026	0.060
Pharmacy costs	-59.33	(73.96)	0.422	0.564	105.80	(68.22)	0.121	0.242
Hospitalization (0/1)	-0.0002	(0.0092)	0.984	0.984	0.0139	(0.0064)	0.030	0.060
Hospital costs	39.70	(208.67)	0.849	0.850	262.71	(168.16)	0.118	0.242

Notes: Cluster-robust standard errors in parentheses. FDR q-values are false-discovery-rate adjusted p-values following Anderson (2008). The FDR q-values are computed separately for fathers and mothers and grouped lottery category and within these four groups for two subgroups, use indicators (GP visit, specialist visit, any medication, hospitalization) and cost factors (GP costs, specialist treatment costs, pharmacy costs, hospital costs). All specifications include controls for gender, ethnicity, age at the first lottery application, fixed effects of the birth year of the applicant and parent, and fixed effects for the lottery category interacted with the year of first lottery.

Table 41: IV-estimates of the effects of being a doctor on parental health care by living distance

	Distance ≤ 40km				Distance > 40km			
	$\hat{\delta}$	s.e.	p-value	FDR q-value	$\hat{\delta}$	s.e.	p-value	FDR q-value
Panel A. Fathers								
Mortality (by 31.12.2019)	0.0011	(0.0136)	0.937	-	0.0086	(0.0140)	0.541	-
Total costs	-113.02	(318.28)	0.723	-	192.36	(322.28)	0.551	-
GP visit	-0.0041	(0.0129)	0.754	0.754	-0.0234	(0.0131)	0.073	0.208
GP costs	-4.46	(4.93)	0.366	0.732	-5.54	(5.20)	0.287	0.574
Specialist visit (0/1)	0.0266	(0.0213)	0.213	0.427	0.0320	(0.0215)	0.137	0.208
Specialist treatment costs	-3.66	(231.12)	0.987	0.988	353.20	(263.41)	0.180	0.574
Any medication	0.0058	(0.0153)	0.705	0.754	0.0014	(0.0159)	0.928	0.929
Pharmacy costs	-106.49	(79.94)	0.183	0.732	47.96	(74.82)	0.522	0.578
Hospitalization (0/1)	0.0099	(0.0077)	0.197	0.427	0.0111	(0.0078)	0.156	0.208
Hospital costs	7.69	(245.01)	0.975	0.988	134.18	(241.05)	0.578	0.578
Panel A. Mothers								
Mortality (by 31.12.2019)	-0.0038	(0.0092)	0.682	-	-0.0140	(0.0101)	0.167	-
Total costs	195.77	(267.33)	0.464	-	477.75	(276.77)	0.084	-
GP visit	0.0021	(0.0116)	0.858	0.859	-0.0070	(0.0121)	0.566	0.567
GP costs	-2.77	(4.63)	0.550	0.682	-2.95	(5.22)	0.572	0.572
Specialist visit (0/1)	-0.0091	(0.0198)	0.645	0.859	0.0205	(0.0210)	0.331	0.471
Specialist treatment costs	222.34	(245.15)	0.364	0.682	95.71	(158.55)	0.546	0.572
Any medication	0.0093	(0.0133)	0.482	0.859	0.0136	(0.0146)	0.353	0.471
Pharmacy costs	34.58	(84.14)	0.681	0.682	67.67	(60.25)	0.261	0.523
Hospitalization (0/1)	0.0044	(0.0073)	0.547	0.859	0.0140	(0.0076)	0.066	0.263
Hospital costs	83.74	(179.00)	0.640	0.682	282.97	(197.04)	0.151	0.523

Notes: Cluster-robust standard errors in parentheses. FDR q-values are false-discovery-rate adjusted p-values following Anderson (2008). The FDR q-values are computed separately for fathers and mothers and by living distance and within these four groups for two subgroups, use indicators (GP visit, specialist visit, any medication, hospitalization) and cost factors (GP costs, specialist treatment costs, pharmacy costs, hospital costs). All specifications include controls for gender, ethnicity, age at the first lottery application, fixed effects of the birth year of the applicant and parent, and fixed effects for the lottery category interacted with the year of first lottery.

Classification of hospital diagnoses and prescription drugs

Table 42: ICD10-codes used to determine main diagnosis in case of hospitalization

Condition	ICD10-code
Respiratory diseases	J00-J99
Abdominal hernia	K40-K46
Chollelthiasis and cholecystitis	K80, K81
Lung cancer	C33, C34
Breast cancer	C50
Prostate cancer	C61
All cancers	C00-C97
Liver cirrhosis	K70, K74.3-K74.6
All circulatory diseases	I00-I99
Hypertensive and cerebrovascular diseases	I10-I15, I60-I69
Heart failure	I11.0, I13.0, I13.2, I13.9, I50
Heart attack	I21, I22, I23
Other ischemic heart diseases	I20, I24, I25

Table 43: ATC4-codes used to identify prescription drug use

Medication	ATC4-code
Peptic ulcer & gastro-oesophageal reflux disease med.	A02B
Diabetes medication	A10A, A10B, A10X
Antithrombotic agents	B01A
Diuretics	C03
Beta-blocking agents	C07
Lipid-modifying agents	C10A, C10B
Corticosteroids	D07A, D07B, D07C, D07X
Penicillins	J01C
Anti-inflammatory/anti-rheumatic medication	M01
Opioids	N02A
Psycholeptics	N05
Antidepressants	N06A
Dementia medication	N06D
Nasal preparations	R01A
Obstructive airway disease medication	R03
Antihistamines	R06A
Anti-infectives	S01A

4.6.2 Event study analysis

Chen et al. (2019) have data on admission lotteries to medical school in Sweden in the years from 2002 to 2010. In those years, 188 applicants were admitted to medical school on the basis of a lottery and 555 applicants were rejected. To study impacts beyond the first eight years after enrollment, they complement the results based on admission lotteries with an event study that compares the health outcomes of doctors' relatives with those of relatives of graduates from law school. Law school graduates are chosen as comparison group because they are similar on dimensions such as income, years of education, secondary school GPA, prestige of the study program and working hours. There may, however, also be dimensions in which they differ, such as interest in study subjects (law vs health), (health-related) lifestyle, partner choice, fertility, etc. Chen et al. (2019) show that in the event study, pre-trends of health outcomes are mostly similar and differences arise around six years after enrolling in medical school. Twenty-five years after starting the study, doctors' relatives have 2 percentage points lower mortality rates than relatives of lawyers.

To assess whether the differences in findings from the admission lottery design between Chen et al's study and ours, carry over to the event study design, we also conducted an event study comparing health care use and mortality of the parents of doctors to those of the parents of lawyers. We focus on the parents of registered doctors born between 1967 and 1996 and construct a control group of parents of lawyers born in the same years. We exclude families where at least one child has a law degree and at least one child is a doctor. If more than one child of the remaining families has a law degree or is a doctor, we only include the oldest sibling in the sample.

For the outcome Y_{it} of parent i in year t, whose oldest child started university education in year τ_i we specify the following regression equation

$$Y_{it} = \alpha_t + \delta_{t-\tau_i} D_i + \gamma_{t-\tau_i} + \eta_i + U_{it} \tag{4.3}$$

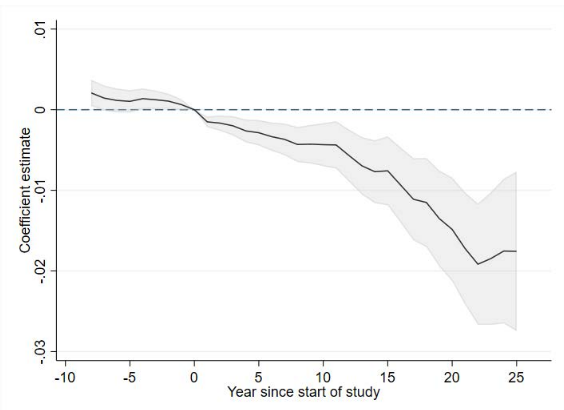
where D_i denotes the child enrolling in medical school compared to law school. Our parameters of interest are $\delta_{t-\tau_i}$, where we normalize $\delta_0 = 0$. We take the year τ_i of enrolling when the child is 19 years old. The general time trend in outcomes is described by $\gamma_{t-\tau_i}$, and α_t are time fixed effects and η_i parent fixed effects. Because mortality is defective, individual fixed effects cannot be used, so we replace η_i by $\theta D_i + X_i\beta$. The vector X_i includes controls for gender and ethnicity of the child and fixed effects for the child's and parent's year of birth. Standard errors are clustered at the level of the parent.

Figure 17 shows the event study results for mortality of the father and mother up to 25 years after matriculation. The results show that after the child started to study, mortality is always significantly lower among the fathers of doctors than among the fathers of lawyers. Mortality is lower among the mothers of doctors than among the mothers of lawyers 16 years after starting the study. These results are very different from the results based on the admission lotteries where we found no effect on parental mortality.

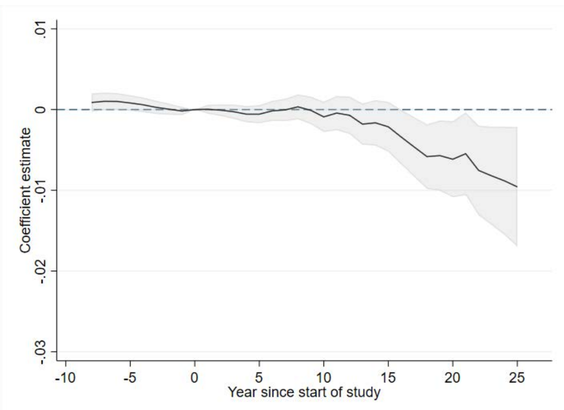
Next, we present similar graphs for total health care costs (Figure 18), hospitalization (Figure 19) and use of prescription medication (Figure 20). The event study shows significant negative effects for total health care costs of fathers and to a lesser extent for mothers. This is not in line with the results from the admission lotteries that did not show an effect on total health care costs for fathers and a positive effect for mothers that is significant at the 10%-level. We do not find effects on the probability to be hospitalized, which concurs with our findings using the admission lotteries. For prescription medication use, the event study shows no effects for fathers, but significantly positive effects for mothers, though not consistently. These findings are again in contrast to the ones we found in Tables 8 and 38 which show no significant differences.

Figure 17: Parents' mortality by year since start study of their child - event study

(a) Fathers



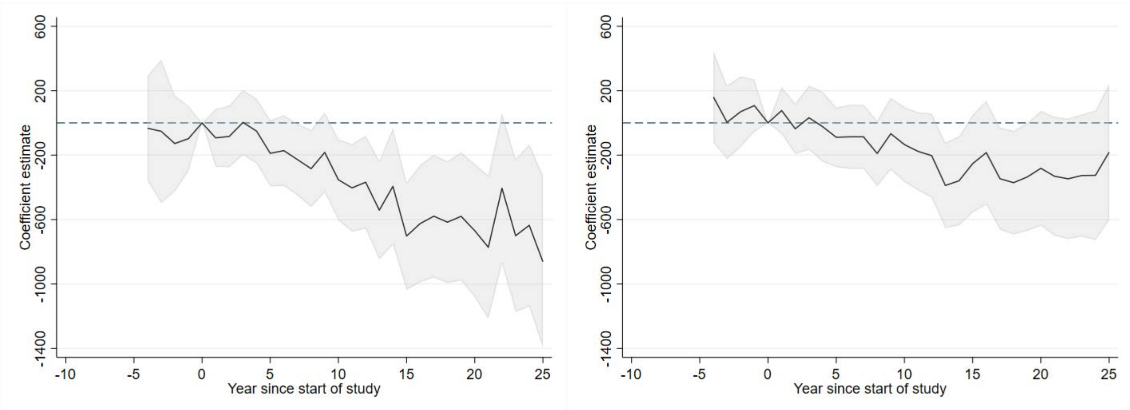
(b) Mothers



Note: Estimates (with confidence intervals) from an event study comparing the parents of doctors and lawyers.

Figure 18: Parents' total health care costs by year since start study of their child - event study

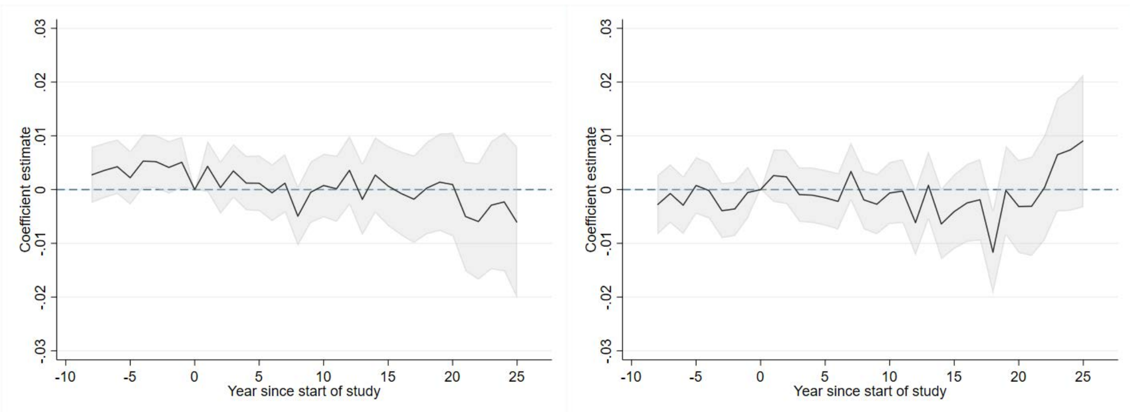
(a) Fathers (b) Mothers



Note: Estimates (with confidence intervals) from an event study comparing the parents of doctors and lawyers.

Figure 19: Parents' hospitalization by year since start study of their child - event study

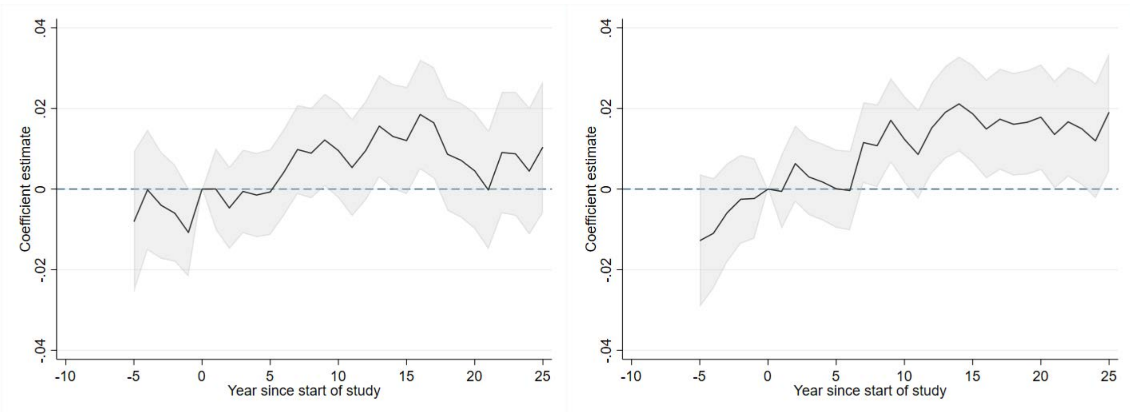
(a) Fathers (b) Mothers



Note: Estimates (with confidence intervals) from an event study comparing the parents of doctors and lawyers.

Figure 20: Parents' medication use by year since start study of their child - event study

(a) Fathers (b) Mothers



Note: Estimates (with confidence intervals) from an event study comparing the parents of doctors and lawyers.

CHAPTER 5

Summary

This thesis consists of three chapters that empirically investigate the effects of educational choices on later-life family outcomes. This chapter summarizes the main results and conclusions from the previous chapters and briefly discusses their policy implications.

Chapter 2 studies the relationship between field of study and family outcomes. It uses administrative data from 16 cohorts of the Dutch population to first document considerable variation by field of study for a range of family outcomes. To estimate causal effects, centrally-executed admission lotteries that created randomization into four oversubscribed study programs are exploited. These programs are medicine, dentistry, veterinary medicine and international business. The estimated effects are based on the contrast between family outcomes of applicants who won the first admission lottery and completed their preferred field of study and family outcomes of applicants who lost the first lottery and ended up in their next-best field. Thereby, the result of the first lottery participation is used as an instrument for study program completion.

The results show that the field of study matters for a range of family outcomes, such as the probability to have a partner, the level and field of education of the partner, fertility as well as earnings of the partner and the household. There is also evidence of intergenerational effects on children's probability to enroll in the highest track of secondary education. The effects are heterogeneous with respect to study program and gender, but the results overall show that field of study does not only affect labor market outcomes but also causally influences other important dimensions of a person's life.

The chapter demonstrates that field of study strongly affects partner choice, in particular for studies that train for a profession with occupational licensing. These matching patterns affect households' resources, but also have some fertility and intergenerational effects, that prospective students should be aware of to make fully informed study choices. The latter ultimately determine how society is shaped and may, for instance, contribute to household income inequality (Eika et al., 2019).

Chapter 3 investigates the role of household specialization based on comparative advantage as a cause of the earnings penalty that women, but not men, experience after having their first child. If household specialization occurs, then the higher-earning partner focuses on labor market work, while the lower-earning partner specializes in child rearing and household production. Using administrative data and applying an event-study methodology centered around the birth of the first child, the chapter first confirms the existence of a large and persistent earnings child penalty on Dutch women, that is predominantly caused by reductions in working hours. It also documents differences in the child penalty by individuals' level of education and field of study.

Importantly, the findings across various proxies for (relative) earnings potential consistently show little evidence of household specialization based on comparative advantage and/or bargaining power. While women's earnings losses and reductions in labor supply are indeed smaller if they have a higher relative earnings capacity, parenthood has hardly any effects on men irrespective of their relative earnings potential. Differences in women's labor market trajectories thus seem to be driven by differences in their absolute earnings potential, such that higher-educated/higher-earning women remain more attached to the workforce after having children. Descriptive evidence indicates that these women make more use of formal child care to combine work and family.

The chapter shows that even in a country where it is possible and presumably accepted that men work part-time, few men do so after the arrival of their first child. This is even true in couples where the mother has a higher earnings potential than the father. Women instead seem to reduce the child penalty — and protect their investment in human capital — by using (formal) child care. Lower-educated women make less use of this option though it is possible that women who want to spend more time with their children invest less in education. The findings from this chapter may have two implications. First, family policies such as paid paternity leave could stimulate men to take on a larger role in child rearing and make them more aware of the labor market potential of mothers. Second, providing sufficient and affordable access to formal child care seems to be important for keeping well-educated women working more than part-time after having children (Andresen and Nix, 2019; Lefebvre and Merrigan, 2008).

Chapter 4 assesses the importance of unequal access to medical expertise and services as a driver of health inequalities. To that end, admission lotteries to medical school in the Netherlands are exploited to estimate the causal effects of having a child who is a doctor on parents' mortality and health care use and costs. Doctors' parents presumably have full access to medical expertise and services via their children, so that their health care is not affected by information limitations.

The findings indicate that having a child who is a doctor has no impact on parents' longevity, while effects on parents' health care use and costs are mostly not significantly different from zero. Further analysis also shows little evidence of heterogeneity by the gender of the child, by the distance between the homes of parent and child and by the child's lottery category. The associations found for the general population and the population of college graduates are thus driven by selection.

The results imply that there are no important spillovers from the medical expertise and connections of doctors to their parents. The Dutch health care system provides sufficient access to people who do not have network connections in the medical sector. The findings also suggest that information interventions aimed to educate people about health risks and preventive behavior may have limited success as a means to lower health care costs in the Netherlands.

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